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An intelligent power distribution service architecture using cloud computing and deep learning techniques

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ABSTRACT

Smart management of power consumption for green living is important for sustainable development. Existing approaches could not provide a complete solution for both smart monitoring of electricity consumption, and also intelligent processing of the collected data effectively. This paper presents a cloud-based intelligent power distribution service architecture, where an intelligent electricity box (IEB) is designed using Zigbee and Raspberry Pi, and a standard MQTT (Message Queuing Telemetry Transport) protocol is used to transfer monitored data to the backend Cloud computing infrastructure using open source software packages. The IEB provides cloud services of real-time electricity information checking, power consumption monitoring, and remote control of switches. The current and historical data are stored in HBase and analyzed using Long Short Term Memory (LSTM). Evaluations and practical usage show that our proposed solution is very efficient in terms of availability, performance, and the deep learning based approach has better prediction accuracy than that of both classical SVR based approach and the latest XGBoost approach.

1. Introduction

Smart building aims to improve quality of life, and working quality by providing convenient and comfortable smart environment (Al-Fuqaha et al., 2015). Traditionally, smart building concentrates on using smart devices and equipment to build and to provide smart services. With the emerging requirements of green life and energy saving, more efforts should be put on managing power distribution and consumption in a smart building, in order to know in advance potential problems such as unusual power usage, power leakage, and so on.

In order to effectively manage electric power systems, the first thing is to collect power usage status, which is achieved with smart metering in an intelligent electricity box (IEB) (Bahmanyar et al., 2016; Depuru et al., 2011). But these IEBs are not fully making use of existing Internet of Things protocols in order to provide effective control and management services, in different network environment. After the collection of the corresponding data, there raises the issue of how to effectively manage, store, process these data. Cloud Computing begins to be used as an effective solution for resolving this issue, as discussed in Grozev et al. (2016). A Smart Home Electricity Management System (SHEMS) using Cloud Computing was proposed in Garcia et al. (2013) to manage power usage data. However, these two didn't provide details on how cloud computing was used to realize scalable data collection, storage, and processing. We are looking for an effective solution scalable to handle large amount of real time collected data. At the same time, the solution should be affordable using open source software packages.

On the other hand, dedicated data mining framework is emerging for electricity power consumption analysis using meter data (Silva et al., 2011). And some begin to use Cloud services to identify outage sources and fault localization, capturing peaks and repeat “offenders” of circuits and transformers, and so on as in Lang et al. (2016). However, the existing data analysis can not accurately predict power usage trend, the existing solutions can be improved by the latest deep learning techniques, as shown in our previous work on analyzing resource requests in a data center (Zhang et al., 2017).

Considering all the above mentioned issues, this paper presents a comprehensive solution and architecture on intelligent power distribution management services using existing network protocols, where a smart power distribution box is designed to take place of conventional

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power distribution boxes, which is used to collect electricity information, power consumption data, and remote control of switching. In addition, power usage data can be transferred via both local area networks and/or Internet, and these data are stored on cloud servers and are used to conduct power consumption behavior analysis. Deep learning (Lecun et al., 2015) based approach (LSTM (Gers et al., 2000) in our current work) is used to conduct accurate analysis of power usage trends.

The contribution of this paper includes:

- We propose a cloud-based architecture supported by a cloud-based computing and storage infrastructure, an IEB to handle power usage, and a data mining engine. This approach can work in various network environment.
- We propose a comprehensive communication solution that combines MQTT (Message Queuing Telemetry Transport) (Thangavel et al., 2014), Zigbee (Farahani, 2008), Wifi, and socket communication, which ensures a unified access to the power usage data across NAT (Network Address Translation), LAN (Local Area Network) and WAN (Wide Area Network).
- LSTM is used for mining power usage data, which can provide very accurate power usage prediction in different situations. We also compared the capabilities of LSTM with that of XGBoost (Chen and Guestrin, 2016), and SVR (Castro-Neto et al., 2009).
- We have extensively evaluated the proposed solution in terms of performance, reliability, extensibility, and accuracy of data prediction, which can be used as a reference solution for similar domains like smart factories.

The rest of the paper is organized as follows. Section 2 presents the architectural design of our solution, including both hardware and software components. Section 3 evaluates our work in terms of performance, reliability, extensibility, and so on. We then review the related work in Section 4. Conclusion and future work end the paper.

2. Architecture design of the proposed solution

Before the design of the cloud-based intelligent power distribution service architecture, we need to make some design decisions (Bass, 2007). These include that:

- Wherever possible, existing Internet of things protocols should be used in order to make the integration of smart devices easier.
- Open source software packages should be used if possible in order to save costs.
- To make the power distribution service available to different platforms, it should support clients on different platforms including IOS, Android, and normal Web clients.
- The power distribution service should be scalable to make it usable in a big building where there may be hundreds of IEBs.
- The power distribution service should be available across different network environment, including networks behind firewall, local area network, and wide area network.

Considering these requirements, we design the overall power distribution service architecture as shown in Fig. 1. It uses MQTT as a protocol for communications between IEB modules, data processing server, and clients, if there is an Internet connection. The IEB consists of a tiny computer (Raspberry Pi[1]), and an expansion board. At the same time, the IEB has switch components which can retrieve electricity parameters including voltage, current, leakage current, power and power factor. These parameters are transfered to the Raspberry Pi, and are then sent to the backend cloud servers via Internet using MQTT. The reason to choose MQTT is that the MQTT-based communication can solve Network Address Translator (NAT) penetration effectively. The cloud servers provide data caching, data storage, data analysis and data query services to users.

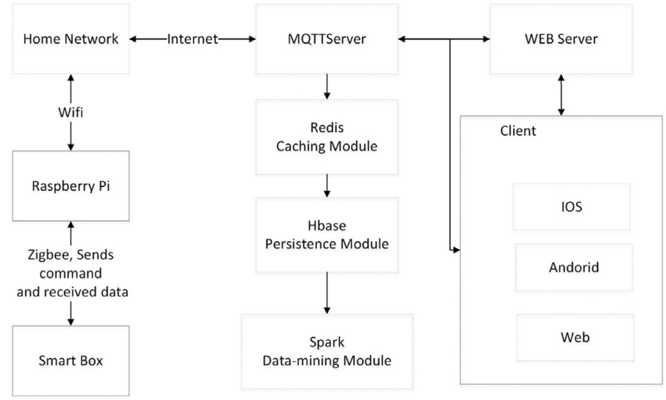

Fig. 1. Schematic diagram of the proposed solution.

Users can use three kinds of platforms to access the power distribution services, including Android, IOS and Web clients, to access and control the IEB and retrieve real-time electricity usage information. The architecture is a layered style, including data collection, communication, storage and analysis module, as shown in Fig. 2.

2.1. Electric unit

An electric unit is the basic element of an Intelligent Electric Box, which mainly contains three parts, namely switch control, data collection and communication. Each electric unit is equipped with an electric metering chip to count and calculate the electric information such as voltage, current, energy and power. Then the electric information is converted into hexadecimal and transfered to Micro Controller Unit (MCU). Similarly, The switch control chip on each electric unit can receive commands from MCU and return switch status to MCU in the form of hexadecimal, and turn the switch on or off according to the commands. The Zigbee chip on each electric unit is an end, which is in charge of exchanging electric information and commands with MCU by wireless communication. There are also sensors like temperature sensor, humidity sensor and leakage sensor in each electric unit, which can detect the environment and guarantee the security of the system.

Raspberry Pi is an ARM based micro computer with Linux operating system running on it, which was chosen as the computing kernel in our system because of its high computing capability and low power consumption. The MCU was customized by adding a real-time clock (RTC), a watching dog and a Zigbee chip to the Raspberry Pi in order to meet our requirements. For example, if MCU can not synchronize time with an Internet time server, it will read the time from the RTC. And the watching dog can monitor the real-time status of the Raspberry Pi and reboot it when there are some serious errors occurred. Different from the Zigbee chip in the electric unit, the Zigbee chip in the MCU is a coordinator, which builds up a network of connected switches and manages this network, and it also receives data from each electric unit and transfers the data to the Raspberry Pi through a serial port. In addition, MySQL database is installed in the Raspberry Pi to store data from one recent week, and it could synchronize data with cloud servers every day.

Generally, there are several electric units and one MCU in an IEB. That is to say, from the network point of view, several terminals and one coordinator establish a self-organizing network, in which each terminal can be recognized by an unique identification, and these identifications are stored on the coordinator, which means that only the registered terminal can join the self-organizing network. As the control center and data transfer station, MCU sends inspection commands to

[1] https://www.raspberrypi.org/.

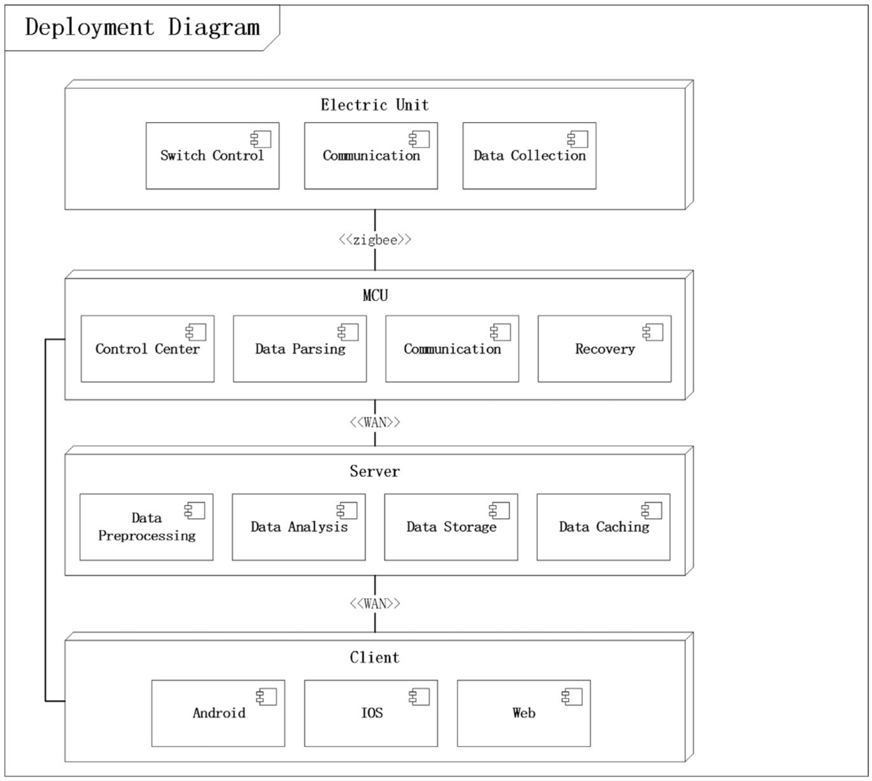

Fig. 2. Deployment diagram of the proposed solution.

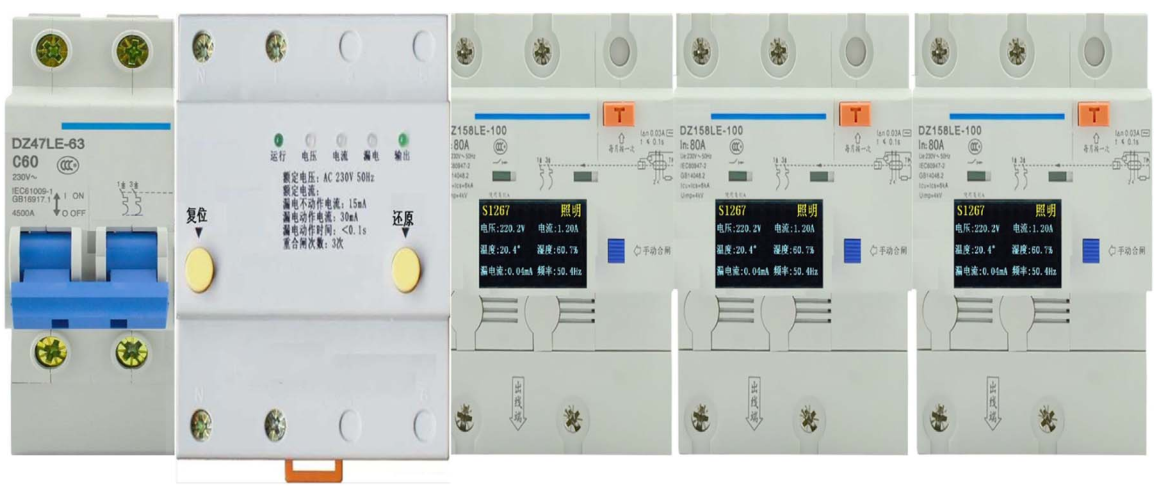

Fig. 3. overview of the intelligent electric power box.

every electric unit in the self-organizing network per hour to get electric information and make sure all the electric units are working well. Meanwhile it can parse the electric information received from electric units and send the data to cloud servers.

Fig. 3 shows an overview of the IEB, where the biggest unit is the one contains the Raspberry Pi as the communication module for the IEB. The IEB control protocol is designed so that the IEB and its clients can understand each other.

2.2. Cloud servers

There are three servers in the intelligent power distribution service architecture, namely communication server, data mining server, and data storage server.

2.2.1. Data management and storage

The IEB we designed collect 14 kinds of power data: Clock, Voltage, Current, Frequency, Electric Energy, Power, Power Factor, Leakage Current, Temperature, Humidity, Switch Status, Alarm Information, Control Commands and Parameter Configuration Commands. As shown in Fig. 4, all the power information is transferred to the Data Caching component which is a Redis[2] buffer and sent to the Local Storage component. The Data Verification component would check data integrity and correctness and send local power data to the cloud servers if it passes checking. We use MySQL database on Raspberry Pi as the local storage component and HBase[3] on the cloud server as the

[2] https://redis.io/topics/introduction.
[3] http://hbase.apache.org/.

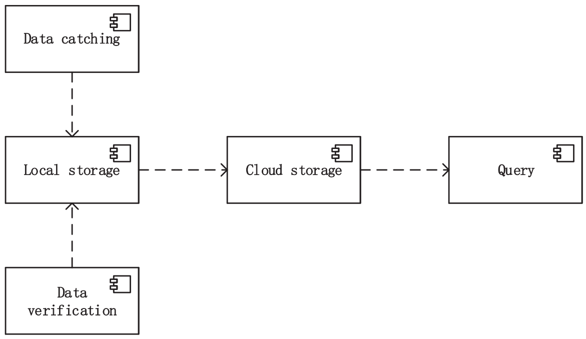

Fig. 4. Component diagram of data management and storage.

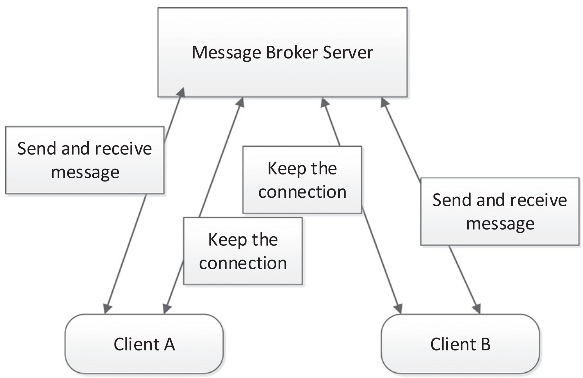

Fig. 5. MQTT Subscribe/publish.

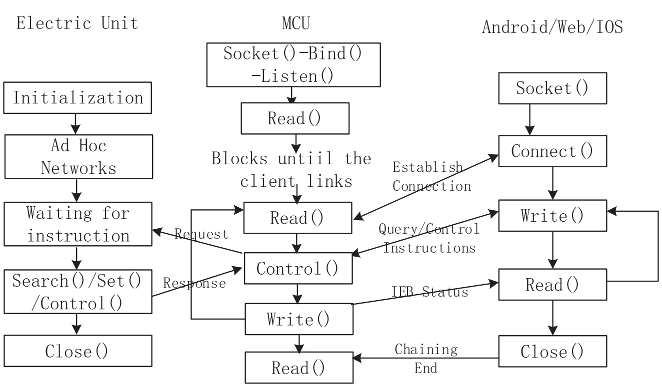

Fig. 6. Socket communication process in LAN environment.

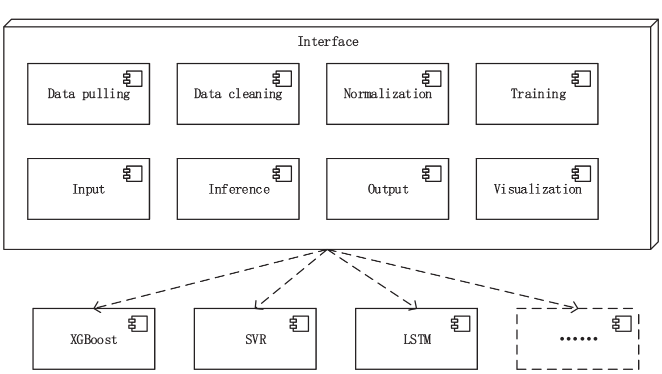

Fig. 7. Component diagram of data mining server.

cloud storage component. We also designed an efficient data query and indexing mechanism for fast data access, which is divided into two parts: the first part is a persistent storage on hard diskthe second part is an index buffer in memory, which stores data indexes because memory can be accessed quickly and efficiently.

2.2.2. Communication server and local area network connections

This architecture considers two network conditions, Intranet and Internet communication, which uses Socket and MQTT protocol respectively. In order to guarantee the security of communication, Apache Apollo[4] proxy server and some encryption algorithms are applied. Fig. 5 shows the subscription and publish process of MQTT messages. In the proposed architecture, MCU, servers, mobile clients and Web clients are publishers and subscribers of each other. The usage of MQTT protocol makes it possible that data packages from MCU can transfer across NAT and deliver to different clients. In this way, we realize a unified communication over both Internet and Intranet (Kim et al., 2015) environment.

The proposed solution can work without any Internet connection, but just local area network (LAN) connections, where clients can control the IEB and electrical appliances. As shown in Fig. 6, we use socket technology to achieve communication between different terminals within the LAN. The communication within the LAN is divided into two parts: MCU and Client. MCU, using a Zigbee module, sends operation instructions to the Electric Unit and collect data from the Electric Unit. MCU has its own wireless module, and sends data to the client side. When an IEB is limited to the LAN, the client automatically matches the LAN IP and communication ports, and creates a long TCP connection, which will communicate with a MCU socket as shown in Fig. 6.

MCU sends operation instructions to the Electric Unit and receives data from it using specially designed control protocol, which have six kinds of instructions, including Inspection, Calendar Configuration, Switch ON/OFF, Unit Parameter Configuration, Coordinator configuration and third-party Appliances Control. Every instruction begins with an 'FF' as its head, followed by 'A*n*', where '*n*' represents the instruction id. The middle part of each instruction is the power information and the last byte is the verification code. Take the Inspection instruction as an example: MCU sends a four bytes' instruction to the Electric Unit: FF, A1, unit address and verification. If the Electric Unit receives and verifies this instruction, it would return twenty bytes data to MCU: FF, A1, unit address, power data (16 bytes) and verification code.

2.2.3. Data mining server

We deploy Spark as the supporting platform for mining power usage data. As shown in Fig. 7, an interface which contains eight components is designed, and three data mining algorithms (XGBoost, SVR, LSTM) are used for analyzing power data. Data pulling component is used to pull both real-time power data from the Electric Unit and historical power data from the cloud storage server. The Data Cleaning component is used to pre-process power data in order to remove noise inside them. Different power data has different scales, the Normalization component is designed to conduct normalization on power data. We also designed a Training component for launching training process for data mining algorithms, in which some hyper parameters such as learning rate and iterations can be configured. The Input and Output components are responsible for data swapping between dataset and data mining algorithms who need rigid data format. After the training process, we can get a model used for predicting power consumption. The Inference component will load and lunch the trained model. The analysis results are shown to users using the Visualization component through line chart, histogram or pie chart. We also provide users with spacial-temporal visualization service. In spacial dimension, regional electricity consumption characteristics can be analyzed according to the residential area. In temporal dimension, annual, quarter and monthly power consumption statistics can be shown to users.

We have three kinds of data mining algorithms suitable for different

[4] http://activemq.apache.org/apollo/.

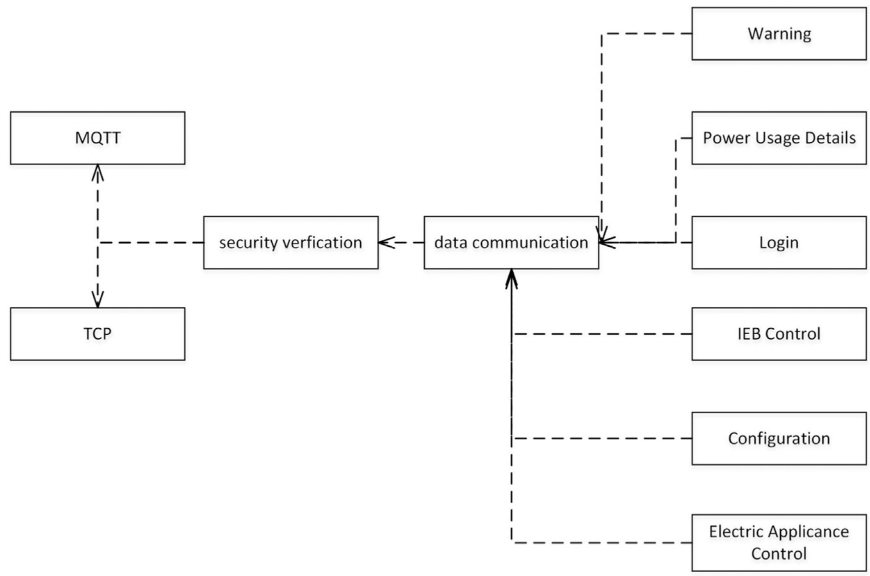

Fig. 8. Architecture of a client.

Table 1
Test bed configurations.

Hardware	Configuration
9 IBM 3650M4 servers	each has 64 GB RAM,24 cores, 12 T storage
Raspberry	Raspberry Pi 2
MCU	CC2530
IOS device	Iphone7
Android phone	OPPOR9
notebookWeb	ASUS PRO551

Table 2
Software packages on IBM servers.

software package	version
Ubuntu	14.04
Hadoop	2.5.2
Hbase	0.98.15
Spark	1.6
Apollo	1.7.1
JDK	1.7

Table 3
Extensibility evaluation.

Clients	10	100	1000	10,000	100,000
time (ms)	3	3.5	4.2	7.1	20.6

situations. For example, SVR can work well under small training sets and can serve as a starting point for understanding power usage prediction. LSTM is a recursive neural network on time serials analysis, and can be used for accurate prediction for power usage trends and patterns, suitable for large amount of data. XGBoost is a choice for both small and big data situation, which has good performance at the same time.

2.3. Clients

There are three type of clients, namely Web based, Android based and IOS based. The architecture of client is shown in Fig. 8.

The client has the following components:

- MQTT component is designed for solving the problem of network penetration.
- TCP communication is used when a user does not have access to the Internet, i.e. only LAN is available.
- Login component is used for connect the IEB to the network. Each IEB has a unique equipment id, and the id will be used for registration, and the priority is given to MQTT communication.
- Switch control component is designed to control IEB switch circuit. The client sends switch operation requests, and after the IEB completes the operation, it will return the IEB status.
- Alarm component is used to provide warning information at emergency situation. When there is power leakage, voltage and current exceed limits, the IEB automatically sends out an alarm information, and the client will receives this alarm information. The alarm is managed according to its severity.
- Power Details Component is designed to handle real-time display of electricity status, and the prediction results of future trend on power usage.
- Configuration component is used to complete the initial configuration of an IEB, access to the home network, adding/deleting an IEB.
- Electric Appliance control component is designed to realize the control of home appliances using a mobile phone.

Table 4
Performance of remote control of IEB.

	1	2	3	4	5	6	7	8	9	10	average
Android(LAN)	1382	1637	1232	1078	1781	1570	1862	1109	1234	1355	1424
Android(WAN)	1720	1229	1366	1773	1169	1860	1073	1203	1589	1421	1440.3
IOS(LAN)	1193	1077	1502	1699	1108	1235	1405	1253	1550	1193	1321.5
IOS(WAN)	1397	1655	1250	1184	1306	1597	1139	1102	1226	1397	1325.3
WEB(LAN)	1641	1566	1392	1441	1276	1055	1006	1942	1245	1852	1441.6
WEB(WAN)	1245	1601	1788	1573	1879	1342	1255	1558	1855	1417	1551.3

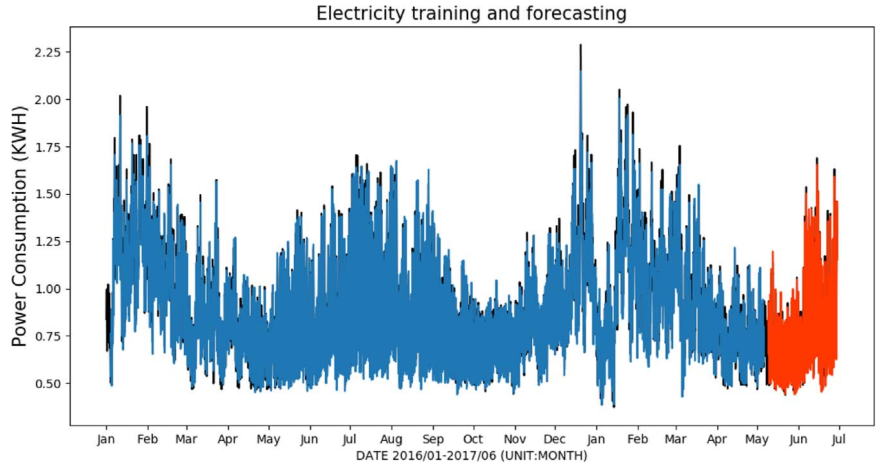

Fig. 9. Visualization of 18 months of electricity consumption (in black), and prediction results (in red). The training used 90% (16.2 months) data (in blue), and the rest of 10% (1.8 months) is the prediction results. The overall RMSE value is 0.04. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Performance of prediction algorithms and their RMSE.

Time period	Running time and RMSE	SVR	XGBOOST	LSTM
04/01–04/10	Time	0.0009	0.0021	0.0054
	Rmse	0.05	0.03	0.03
10/01–10/10	Time	0.0011	0.0025	0.0083
	Rmse	0.04	0.02	0.02
07/01–07/10	Time	0.001	0.0024	0.0066
	Rmse	0.08	0.03	0.03
12/16–12/25	Time	0.0012	0.0027	0.0056
	Rmse	0.07	0.06	0.04
01/11–01/20	Time	0.0012	0.0025	0.0064
	Rmse	0.05	0.03	0.03
06/01–06/10	Time	0.0118	0.0024	0.0055
	Rmse	0.09	0.03	0.03

3. Evaluations

We have extensively evaluated the proposed solution for its reliability, extensibility, performance, and also the accuracy of prediction of power usage, in order to make sure that our approach is applicable to real industry and commercial situations. The hardware and software configuration of our test bed is listed in Tables 1, 2.

3.1. Reliability

For testing the reliability, we have made the whole system (IEB, backend cloud servers) running continuously for 6 months in a building. Till now, it does not have any problems, for both hardware and software components All operations on IEB (control IEB, read data) are successful, and the analysis of the collected data is running reliably.

3.2. Extensibility

We have tested the extensibility of the proposed solution in the Internet connection environment. In such a case, real-time communication and stability are closely related to the MQTT server. In order to make sure that our approach can work in a moderate scale, e.g. tens of thousands connections in a small city scale, we simulate these IEB connections by multiple PC clients sending data (100 Bytes, as the data interchange to a MQTT server is 100 bytes at the most for the current design of IEB control protocol) in parallel. We show the measurements in Table 3. Obviously we can see that when there are 100,000 clients publish MQTT messages to the server, it can handle all these parallel requests at real time (around 20 ms).

3.3. Performance

In order to make sure the usability of the remote control of IEB, we have extensively evaluated its performance, where in Table 4 we show one of its 10 measurements. We record the round trip time taken between a client request and IEB response corresponding to this request. Interestingly we can see that the Android client is a bit slower than the IOS client. For all the clients, it takes around 1.5 s for the remote control of the IEB, which is quite OK as these kind of operations are not time critical.

3.4. Prediction of power usage trends

We use the designed IEB to collect power usage information for 16 months in an apartment. In order to know the power usage trend, we use SVR, XGBoost and LSTM for predicting electricity power usage. Ninety percent of the data are selected for training and the remaining ten percent are used to test the prediction. All three algorithms can be used to predict how many hours of electricity will be used as output in the future, based on historical data of electricity power usage per hours as input. We use the previous (3,5,6,7,15,24,48) hours of electricity consumption as inputs, and predict the next ten days of electricity consumption. After training and optimization, we found that SVR, XGBoost and LSTM performs the best when the inputs of previous length time are 6,7,24 hours respectively.

We show the history of electricity power consumption data visually as in Fig. 9. We can see that the consumption in April and October is the lowest, with an average around 0.6 KWH per hour. In July and December, it has the highest consumption, with an average of 1.2 KWH per hour. In January and June, the consumption is less stable. Therefore we choose six representative electricity consumption period (namely 04/01–04/10, 10/01–10/10, 7/01–07/10, 12/16-12/25, 01/11-01/20, 06/01–06/10) and conduct prediction for the next ten days as shown in Fig. 9.

We also test the running time of the SVR, XGBoost and LSTM. Standard deviation (Root Mean Square Error-RMSE) of the predicted and the actual is used to show the effectiveness of these three algorithms, as shown in Table 5 .

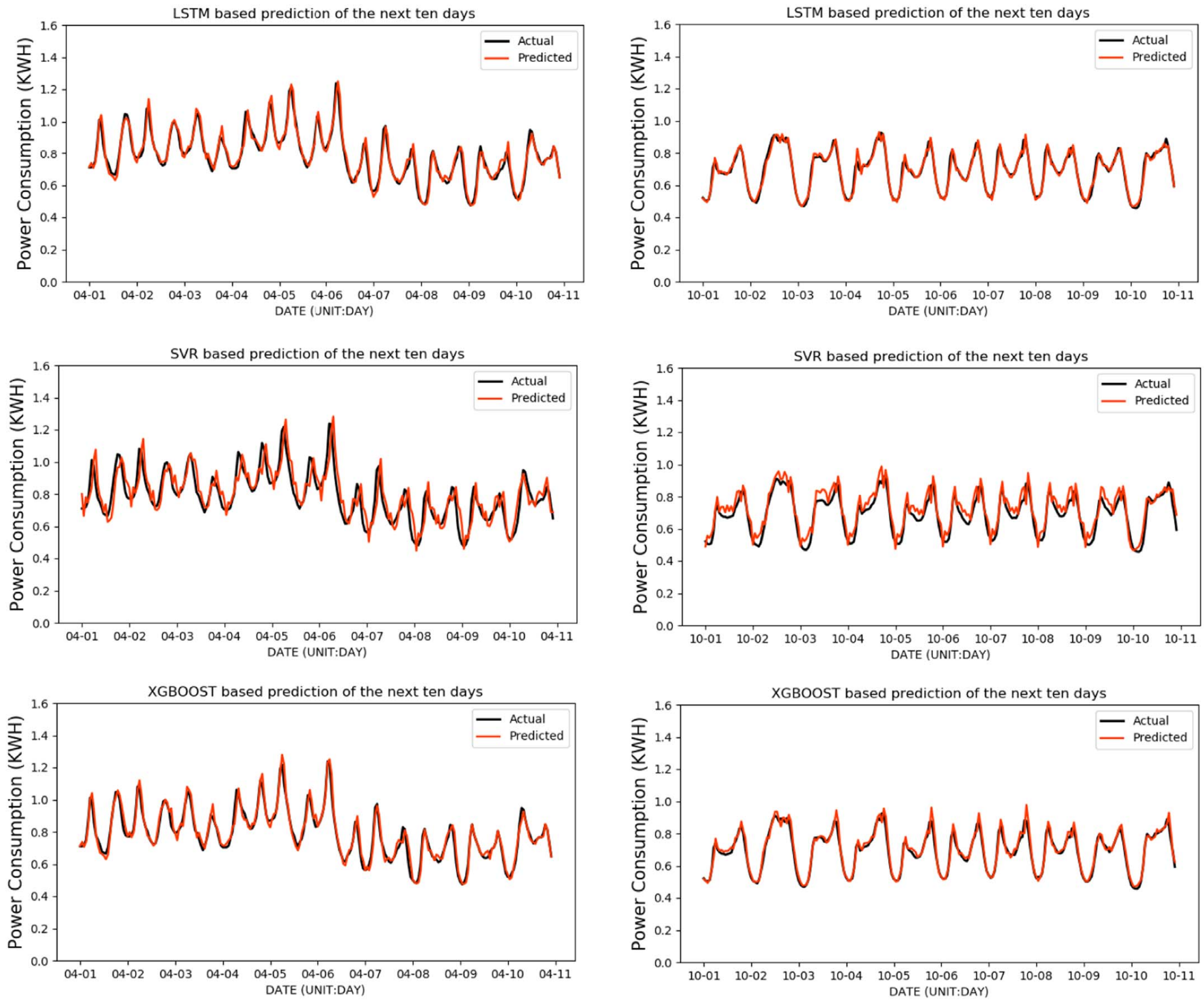

Fig. 10. LSTM, SVR, XGBoost based prediction of power usage for the next 10 days in power trough situation.

From Table 5, Fig. 11, Fig. 10 and Fig. 12, we can see that the standard error of SVR is relatively high, which ranges 0.04–0.09, especially for the peak usage of power in July and December. The standard error of XGBOOST is OK, and its RMSE value ranges between 0.02 and 0.06. There is a relatively big gap for the predicted value and the actual value when there is a sudden increase in July. The RMSE value of LSTM is between 0.02 and 0.04, and obviously we can see that LSTM based approach can accurately predict the power usage for all the three different situations.

4. Related work

There is only a very brief discussion on using Cloud Computing for managing electrical power system in Grozev et al. (2016), without any details on how to use it nor implementation details. In our work, we propose a comprehensive solution for effective power usage monitoring and management, including data collection, data management and mining, where commonly used protocols (Mahmood et al., 2015) are chosen to make the design repeatable and affordable by researchers and manufacturers.

Smart metering has been a research topic for some time, e.g. the work in Bahmanyar et al. (2016), Depuru et al. (2011). The work in Depuru et al. (2011) presents extensive discussions on challenges and issues for smart metering. In our work, we have designed the smart metering using existing protocols and cost-effective hardware, which is an end point for collecting data. Additionally we want to make use of these data for smart management of power usage.

Cloud computing based power grid data analysis provides promising features for identifying outage sources and fault locations, capturing peaks and repeat “offenders” of circuits and transformers, as shown in Lang et al. (2016). We are developing our solution from an end-user point of view instead of from an power plant point of view. We use LSTM, SVR, XGBoost to provide accurate prediction on power usage trends.

The work in Silva et al. (2011) provides a very interesting approach on using autonomous learning based data mining framework for power

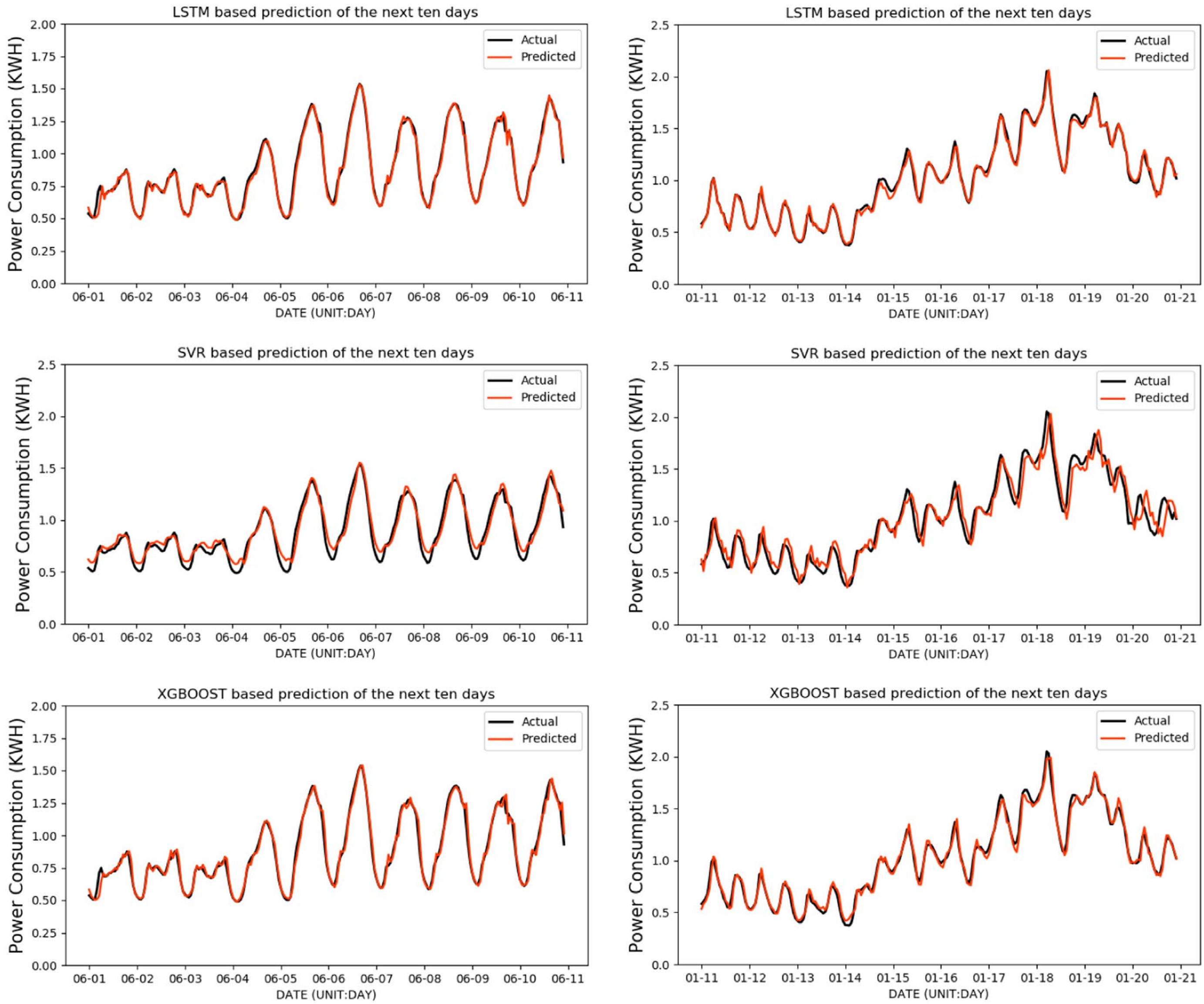

Fig. 11. LSTM, SVR, XGBoost based prediction of power usage for the next 10 days in power peak situation.

consumption analysis, where past learning results can incrementally be used to acquire new knowledge. In our work, we use unsupervised learning, namely LSTM to predict power usage trends. We also target to provide a comprehensive solution including an IEB, data storage and management using cloud computing, and data analysis using the latest algorithms.

Another closely related work to ours is the Smart Home Electricity Management System using Cloud Computing (SHEMS) proposed in Garcia et al. (2013). Its electronic switches are not the same as ours, and they do not have wireless communication capabilities. The mining of the collected power data was not considered either.

An extensive survey on energy big data is presented in Jiang et al. (2016), where an integrated big data architecture in the smart grid is proposed. This architecture has similarity on big data storage with ours, but we have additionally extensive support for big data mining using latest algorithms.

Crowd-sourced data control is also proposed to solve the big energy data problems (Jiang et al., 2016). This crowd-sourced idea can be further improved by crowd sensing as the work in Guo et al., (),Guo et al. (2017). Currently we have not applied crowd-sourcing idea in our work, but in the future we will extend our work by mobile crowd-sourcing to pre-process the sensed data, in order to improve the data quality.

5. Conclusions and future work

Effectively monitoring electricity power status and conducting smart management of power consumption, are very important for achieving green living. The existing work focus either on monitoring power usage using an intelligent electricity box, or providing a data mining framework, which could not provide a complete and efficient solution for monitoring power consumption. This paper presents an intelligent power distribution service architecture, where an intelligent electricity box is designed to work seamlessly in NAT, LAN, WAN environment. Standard MQTT protocol is used to transfer monitored data to the backend Cloud infrastructure. The current and historical power status and usage data are stored in HBase and analyzed and compared using LSTM, SVR and XGBoost. Extensive evaluations and

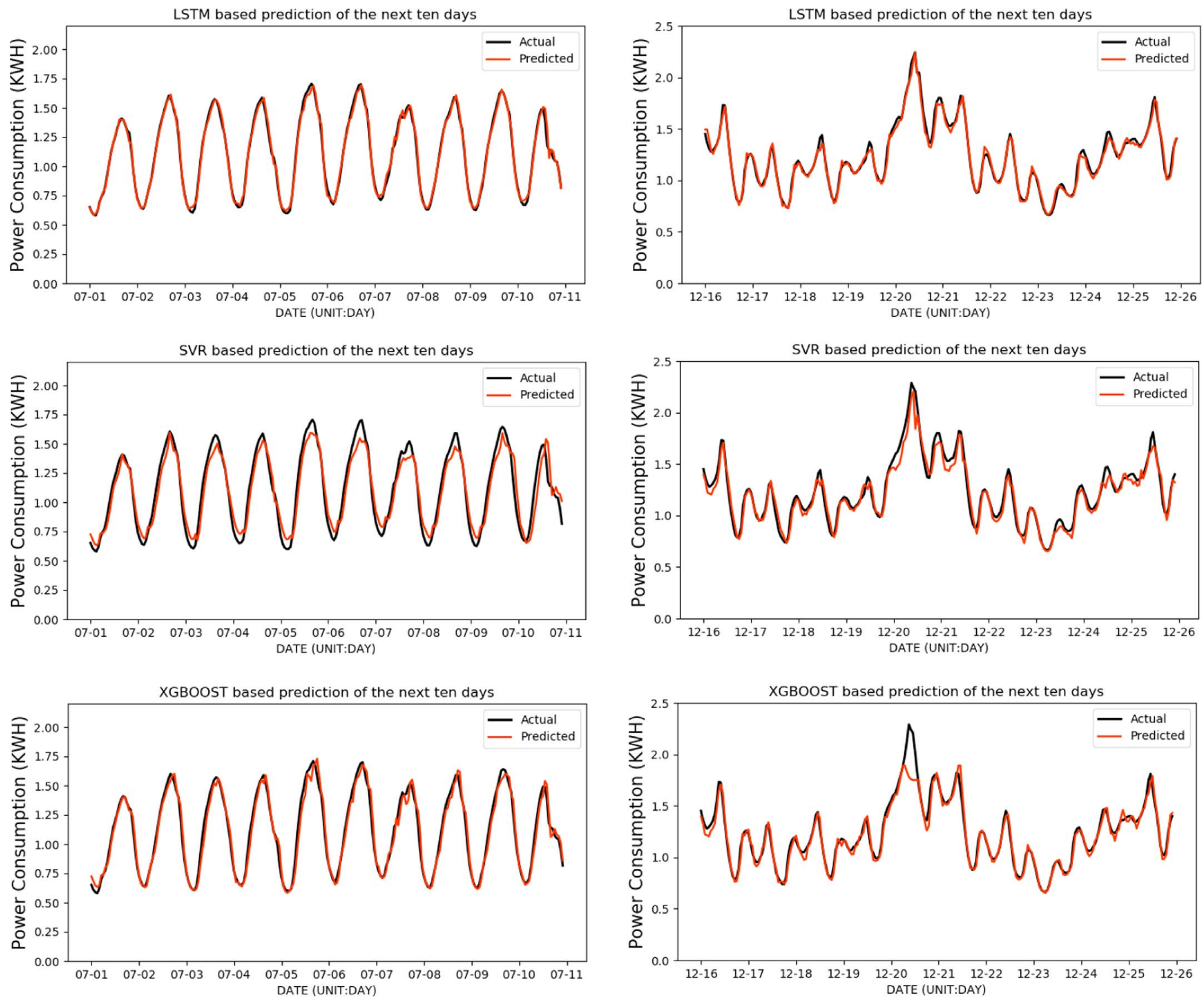

Fig. 12. LSTM, SVR, XGBoost based prediction of power usage for the next 10 days in peak fluctuation situation.

practical usage show that our proposed solution has high availability, extensibility, good performance, and the deep learning based approach achieves accurate prediction on power usage trend.

In the future, we will use more deep learning techniques in the data mining component, e.g. Deep Belief Network (Zhang et al., 2015). Evaluations will be done on a larger scale when the IEB goes to broad market. It will be interesting to collaborate with the China Grid on mining situations like stealing of electric power.

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