

# A Deep Belief Network for Electricity Utilisation Feature Analysis of Air Conditioners Using a Smart IoT Platform

Wei Song\*, Ning Feng\*, Yifei Tian\*, Simon Fong\*\*, and Kyungeun Cho\*\*\*

## Abstract

Currently, electricity consumption and feedback mechanisms are being widely researched in Internet of Things (IoT) areas to realise power consumption monitoring and management through the remote control of appliances. This paper aims to develop a smart electricity utilisation IoT platform with a deep belief network for electricity utilisation feature modelling. In the end node of electricity utilisation, a smart monitoring and control module is developed for automatically operating air conditioners with a gateway, which connects and controls the appliances through an embedded ZigBee solution. To collect electricity consumption data, a programmable smart IoT gateway is developed to connect an IoT cloud server of smart electricity utilisation via the Internet and report the operational parameters and working states. The cloud platform manages the behaviour planning functions of the energy-saving strategies based on the power consumption features analysed by a deep belief network algorithm, which enables the automatic classification of the electricity utilisation situation. Besides increasing the user's comfort and improving the user's experience, the established feature models provide reliable information and effective control suggestions for power reduction by refining the air conditioner operation habits of each house. In addition, several data visualisation technologies are utilised to present the power consumption datasets intuitively.

## Keywords

Cloud Computing, Deep Belief Network, IoT, Power Conservation, Smart Metre

## 1. Introduction

Conventionally, surveillance and analysis of electricity consumption are essential methods for saving energy, especially for air conditioners, the energy consumption of which makes up the largest proportion of the household electricity bill [1]. To enhance the user's experience and comfort in offices and residences, automatic management systems of air conditioners are widely researched by utilising several technologies, such as Internet of Things (IoT), automatic control, and cloud computing, to realise smart temperature adjustment [2]. To increase the energy utilisation efficiency of air conditioners, this paper proposes a smart electricity utilisation IoT platform with a deep belief network

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(DBN) to estimate the electricity utilisation feature of user behaviour. In the platform, smart metres and smart gateways are developed to realise bi-directional communication between air conditioners and a cloud server. A smart metre detects the power consumption of the air conditioner connected to it at a certain time interval and reports the discrete dataset to the cloud server via an Internet protocol. In addition, manual control signals from remote mobile phones are transmitted to individual metres through the corresponding gateways [3]. In the cloud server, two strategies are executed to save energy: remote control of domestic air conditioners and automatic behaviour planning based on the user's habits [4].

In the recent years, a massive amount of research has been conducted on real-time surveillance and feedback mechanisms in the IoT domain to reduce electricity consumption [5]. On the demand side, several operational interfaces are provided to achieve remote monitoring and control, such as remote trigger control, electricity parameter uploading, and electricity burden notification [6]. On the supply side, after analysing current and historic power datasets collected in a certain area, an optimum strategy of electricity allocation is implemented to adapt to the dynamic energy consumption. To satisfy the requirements of both the demand and supply sides, we integrate surveillance machines with wireless transmission to realise a smart electricity utilisation network [7]. In this network, the real-time information of electricity consumption in a whole city is shared for the analysis energy datasets and behaviour planning [8].

To realise the smart control of air conditioners, a smart metre is developed to modify the operational parameters after analysing the environmental information collected by the embedded sensors. Meanwhile, with the continuous increase of energy consumption, several effective methods are recommended to reduce the electricity burden on the supply side, such as peak load shifting and power brownouts. The smart meters are utilised to transmit the environment information to the cloud server, where deep learning algorithms are implemented to optimise the electricity strategy [9].

The proposed smart electricity utilisation IoT platform integrates interdisciplinary technologies, including embedded hardware development, wireless communication, data mining, and smart control. This platform not only supports remote control and monitoring but also realises power reduction strategies using a DBN learning algorithm. In addition, the platform provides an interactive data visualisation interface to display the online and offline power utilisations for intuitive monitoring.

This paper is organised as follows: Section 2 discusses the related works on smart power utilisation methods; in Section 3, the proposed smart electricity utilisation IoT platform is described; in Section 4, the DBN algorithm of electricity utilisation feature modelling is presented; in Section 5, we analyse the performance of the proposed IoT platform with the DBN algorithm; and Section 6 concludes this paper.

## 2. Related Works

According to the energy consumption statistics of the European Union, the electricity waste of air conditioners comprises a large proportion of the total greenhouse gas emissions. Saha et al. [10] proposed a smart-home energy management system to manage users' demand using a smart hardware network. This system enabled automatic correction when failures occurred in communication and data processing. To increase the power utilisation efficiency, special approaches were implemented in summer and winter based on the different air conditioner usage habits. Zhou et al. [11] utilised

renewable energy resources in domestic power management systems, such as solar and wind power management systems. In this system, an energy monitoring module measured and reported the real-time energy consumption. To decrease the electricity bill, this system automatically controlled the appliances to operate in low-power states. However, environmental sensors were not embedded in these systems, so the operation of the appliances could not effectively respond to environment changes [12].

Conventionally, automatic building systems contained several smart controlling functions, such as remote monitoring, ubiquitous control and energy optimisation [13]. Burgess and Nye [14] developed an open and transparent system of electricity surveillance, which recorded the whole power utilisation process, including purchase, manufacture, and usage of customers. These records provided a reliable mathematical model for energy circulation. Marinakis et al. [15] proposed a Dupline-based interactive energy management solution to achieve smart control using environment sensors to adapt to indoor and outdoor situations without affecting users' experiences.

With the rapid development of Internet technologies, network equipment increasingly supported remote control and monitoring, which had enormous market potential. In the communication module between intelligent terminals and smart gateways, wireless local area networks (WLANs) exhibited low energy consumption. For improvement of energy utilisation, Liu [16] implemented a ZigBee protocol to reduce electricity waste in the data transmission process. Compared with other ad hoc networks, the ZigBee protocol had several advantages such as lower electricity consumption and wider available range. In a smart house, the low data transfer rate satisfied the transmission demand of the environmental information collected by sensors. To integrate air conditioners into a wireless network, Gill et al. [17] developed an automatic system of electricity management using a ZigBee protocol. A local area network (LAN) of domestic electrical equipment was established through a ZigBee communication module, where the intelligent terminals and the environmental sensors were connected with a smart gateway. This system not only managed air conditioners with smart strategies, but also supported remote manual control with a data visualisation interface. Although these systems optimised energy utilisation, the controlling server in the local management system wasted additional electricity, which resulted in a massive increase in the household electricity bill.

To reduce this additional energy consumption, Shang et al. [18] proposed an IoT solution that used smart gateways to transmit sensors signals, which replaced the central server in the smart home. This way, the connections between smart metres and appliances were enabled via the wireless network. Meanwhile, the remote signals received by the gateway were delivered to the corresponding metres for appliance control. Using a ZigBee protocol, Han et al. [19] developed a remote energy-saving system to reduce the power consumption of home appliances. To increase the energy utilisation efficiency, a manually supported remote control interface based on the monitoring voltage detected by a power monitoring circuit was used. However, these manual remote control approaches only depended on voluntary information and did not support the responses of centre controlling server, so the power conservation effects were reduced.

Yang and Lee [20] described a statistical approach to collect consumption features of the appliances and users' habits for establishing optimised strategies under different circumstances. In an individual family, this electricity consumption saving strategy was based on automatic matching with scheduling tables. In a certain period and area, the estimation of total electricity consumption was essential for both users and the supply side. The power station was able to generate an appropriate amount of electricity to reduce waste. Paetz et al. [21] collected electricity utilisation habits from 29 persons and analysed

their responses to different energy-saving strategies. Although the testing strategies saved energy and reduced financial expenses, few users felt comfortable abandoning flexible usage habits.

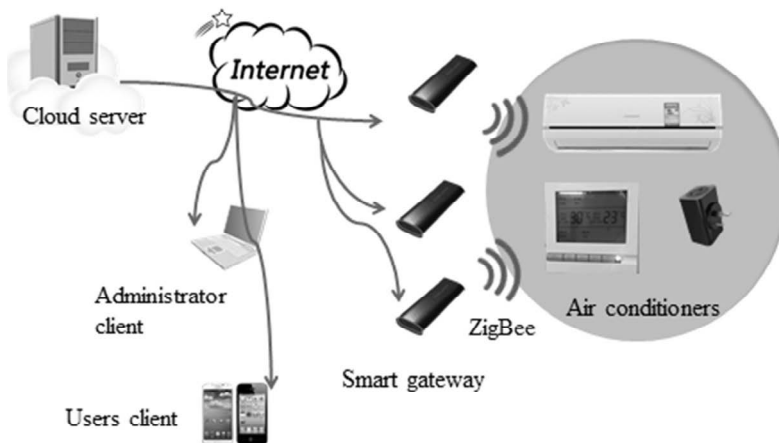
To reduce energy consumption, smart metres and smart air conditioners were utilised in smart homes. To raise awareness about energy conservation, Xu et al. [22] connected smart metres with smart phones to display the real-time electricity consumptions of home appliances. Mital et al. [23] transmitted electricity datasets that were gathered by smart metres in a certain community to a computation centre via a wireless network. In the centre, the power demands were analysed in real time so that the power station generated a suitable amount of electricity to avoid extra waste. This approach ignored the manual control interfaces of remote mobile phones, especially for high-power electrical equipment.

To achieve overall management on the supply and demand sides, real-time big data stream mining is widely utilised in IoT and cloud computation for analysing the current energy usage [24]. Wang et al. [25] proposed a particle swarm optimisation algorithm for optimising the electricity strategy to reduce the power utilisation cost without decreasing the comfort of the user. This algorithm provided the feedback of available information on energy consumption to the administrator of the smart home. Chou and Telaga [26] developed a mixed neural network to establish an electricity utilisation model for monitoring consumption anomalies.

To provide electricity utilisation strategies, this paper develops a smart IoT platform with a DBN algorithm, which generates electricity utilisation feature models of air conditioners. The proposed platform is able to modify operation parameters autonomously based on the analysis results of electricity consumption datasets reported from the distributed gateways.

### 3. Smart Electricity Utilisation IoT Platform

To achieve the smart control of air conditioners, this paper develops a smart electricity utilisation IoT platform, as shown in Fig. 1, which contains remote and automatic operation, power consumption analysis and data visualisation functions.



**Fig. 1.** The proposed smart electricity utilisation IoT platform.

Compared with other wireless protocols, such as Bluetooth and Wi-Fi, the ZigBee protocol has several advantages, such as low cost and low energy consumption, which are useful for wireless communication in a smart home. In our local wireless network, smart metres connected with air conditioners transmit power consumption data to the gateway based on the ZigBee protocol while receiving remote control signals from the gateway. In the metres, several sensors are embedded into the smart metres to detect environmental information such as temperature and humidity which is essential for estimating the current environmental situation. The developed smart gateway is considered the intermediate equipment in the platform for dataset transmission and protocol conversion of ZigBee/Internet. The power consumption datasets and remote control signals are delivered using the gateway between air conditioners and the cloud server. The metre has a computation unit to analyse the current environmental state and control commands from the gateway. Then, the gateway sends an adaptive operation signal from the unit to its connected air conditioner.

The smart metres record the power consumption, environmental information and other electricity utilisation data in real time, which are transmitted to the connected gateway with the ZigBee protocol at a certain time interval. The gateway delivers these received datasets to the cloud server for data storage and behaviour feature analysis. The server also receives remote control signals which are transmitted from mobile devices via the Internet. Based on the current environmental temperature and humidity displayed by their mobile devices, the users are able to remotely control their air conditioners using manual instructions, such as switching air conditioners, changing the wind mode and modifying the pre-set temperature. The corresponding gateway receives the control signals transmitted from the cloud server based on its IP address. In addition to air conditioners, the gateway is able to communicate with other smart appliances supported by the ZigBee protocol.

As the intermediary between the mobile terminal and smart metres, the cloud server is mainly responsible for transmitting control signals and generating behaviour plans for energy conservation. The remotely issued instructions are delivered to the corresponding air conditioners to modify the operating situation. When query requests from mobile devices are received, the cloud server distributes the demanded datasets to the relevant gateway connected with the destination air conditioners. After collecting the distributed electricity consumption information, the cloud server analyses users' power utilisation features and provides electricity-saving strategies.

## 4. Deep Belief Network

In the cloud server, a DBN algorithm is applied to analyse the energy consumption and establish the user's electricity utilisation features. The DBN comprises a multi-layer restricted Boltzmann machine (RBM) as a stochastic neural network [27]. As shown in Fig. 2, the DBN mechanism comprises a visible layer, a set of hidden layers and an output interface. The training process of the DBN includes a pre-training phase and a fine-tuning phase.

The pre-training phase aims to approximate the model parameters. In the pre-training phase, the DBN nodes are divided into pairs to form the RBM, as shown in Fig. 3. The output of the lower-layer RBM, which is trained independently, is utilised as the input of its higher-layer RBM. After the DBN layers are independently trained, a covariance function of the Gaussian process is initialised based on the RBM, which is then fine-tuned by back propagation (BP). The BP network receives the output

vector of the RBM as the input feature vector while the entity relation classifier is trained with supervision. Because the mapping from the weights to the feature vectors of the RBM is locally optimum in this layer rather than globally optimum in the DBN, the BP network with a loss function is applied in the fine-tuning process of each layer of the RBM from top to bottom. The loss function is expressed in (1), where  $x$  is the vector of actual values of the training data and  $x'$  is the vector of values estimated by the DBN. Finally, the minimum-error estimate is obtained by the repeated reverse learning process.

$$L(x - x') = \|x - x'\|_2^2 \tag{1}$$

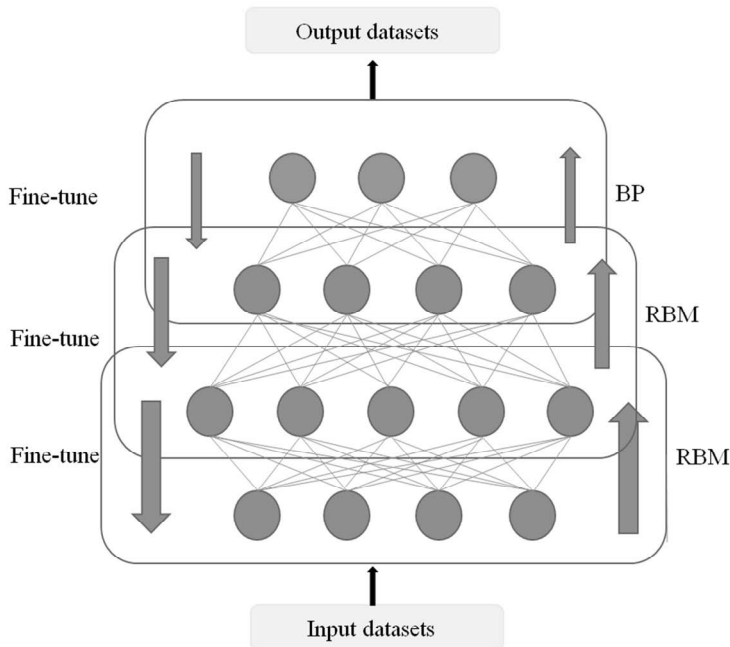


Fig. 2. The multi-layer DBN mechanism.

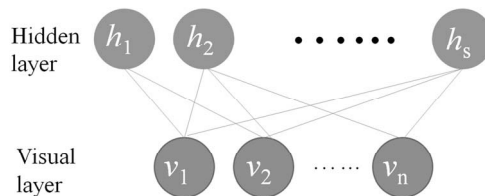


Fig. 3. An illustration of the RBM.

As a categoriser, a Softmax regression algorithm is utilised in the top layer of the DBN to realise multi-category classification. For a given test input  $x$ , the probability of each classification of the test data  $x$  is estimated. An RBM comprises a visible layer  $V = (v_1, v_2, \dots, v_n)$  and a hidden layer  $H = (h_1, h_2, \dots, h_n)$ . Each visible element is associated with a hidden element and a bi-directional weight. Eq. (2)

presents the energy function of the RBM between the visible layer and hidden layer, where  $\delta$  is a coefficient set ( $W, a, b$ ) of the RBM; the parameters  $a_i$  and  $b_j$  are the bias values of the  $i$ th visible and the  $j$ th hidden variables, respectively; and  $w_{ij}$  is the weight of the edge between elements  $v_i$  and  $h_j$ .

$$E(v, h, \delta) = -\sum_i \sum_j w_{ij} v_i h_j - \sum_i a_i v_i - \sum_j b_j h_j \quad (2)$$

The joint probability function of a given  $(v, h)$  is expressed as

$$P(v, h, \delta) = \frac{e^{-E(v, h; \delta)}}{\sum_i e^{-E(v_i, h; \delta)}} \quad (3)$$

In an RBM, the probability that the  $j$ th hidden-layer neuron is activated is formulated as

$$P(h_j | v) = \sigma(a_j + \sum_i w_{ij} v_i) \quad (4)$$

Due to the bi-directional connection, the probability that the  $i$ th visible element is activated by the corresponding hidden element is derived as Eq. (5), where  $\sigma(c) = (1 + e^{-c})^{-1}$  is the sigmoid activation function.

$$P(v_i | h) = \sigma(b_j + \sum_i w_{ij} h_i) \quad (5)$$

When data  $x$  is assigned to the visible layer, the RBM calculates the probability of every hidden element ( $h_j|x$ ). If the probability of a hidden element is greater than a threshold, this element is activated, which is denoted as  $h_j=1$ ; otherwise, it is not activated and  $h_j=0$ .

Using a gradient ascent of maximum likelihood estimation, the RBM utilises an iterative method to update the optimisation parameters. The maximum likelihood function is formulated as

$$P(V | \delta) = \frac{1}{\sigma(\delta)} \sum_h e^{-E(v, h; \delta)} \quad (6)$$

The iterative formula of the parameter  $\delta(W, a, b)$  is  $\delta = \delta + l \cdot \frac{\partial \ln L}{\partial \delta}$ , where  $l$  is the learning rate of the pre-training. To improve the training efficiency of the RBM, the contrastive divergence learning method is utilised with a Gibbs sampling algorithm in the training process, which is implemented via the following steps:

- Select  $x_1$  as a sample from the training dataset for the RBM.
- Compute the probability that every hidden element is activated  $P(h_1|v_1)$ . The sample  $h_1$  is extracted based on the probability distribution by Gibbs sampling.
- Reconstruct the visible layer with  $h_1$  and compute the activation probability of every visible element  $P(v_2|h_1)$ .
- Extract sample  $v_2$  by Gibbs sampling.
- Compute the activation probability of every hidden element  $P(v_2|h_2)$ .

- Update the weights and biases of the RBM by

$$W \leftarrow W + \lambda(P(h_1 | v_1)v_1 - P(h_2 | v_2)v_2),$$

$$a \leftarrow a + \lambda(v_1 - v_2),$$

$$b \leftarrow b + \lambda(h_1 - h_2).$$

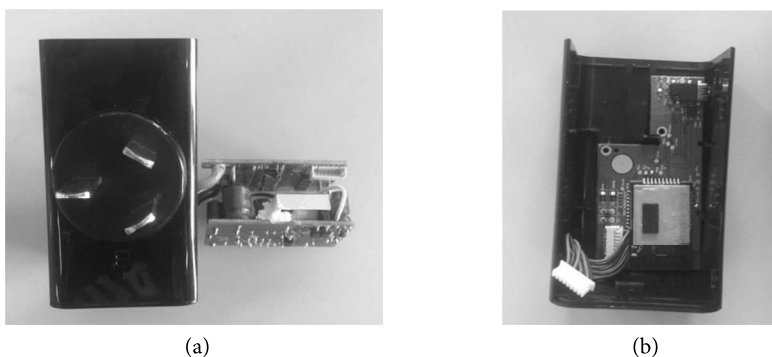
- After several rounds of training, the hidden layer is able to represent the features of the visible layer.

## 5. Experiments and Analysis

In this section, we analyse the performance of the proposed smart electricity utilisation IoT platform for air conditioners with the DBN algorithm. The system was tested on more than 300 air conditioners installed in offices, hotels and homes. The electricity utilisation information was collected for more than 1 month.

### 5.1 Performance of the Electricity Utilisation IoT Platform

The developed smart metre for air conditioners included an electricity measurement module and a ZigBee communication module, as shown in Fig. 4. The electricity measurement module supported AC-DC conversion based on the power supply specifications of the air conditioners. An energy measurement chip was utilised to calibrate several electrical parameters, including voltage, current, frequency, active power, reactive power, apparent power, power factor, active energy and reactive energy. These datasets were converted to the corresponding electrical signals and transmitted to the gateway using a ZigBee communication module. After receiving control signals from the ZigBee node, the smart meters executed an automatic management function to modify the relevant operations of air conditioners. An infrared transceiver was able to determine the device type based on an equipment library when it received the control signals, such as switching, adjustments of wind speed and pre-set temperature. Meanwhile, a multi-sensor module was integrated on the back side of the ZigBee communication module, which detected temperature and humidity information.



**Fig. 4.** The developed smart meter for air conditioner control. (a) Electricity measurement module and (b) ZigBee communication module.

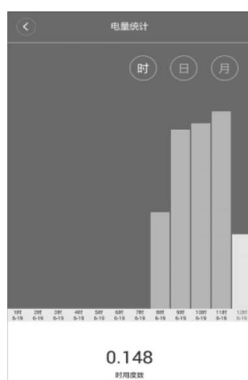


Fig. 5 shows our applied router and the smart gateway for connecting the air conditioners to the Internet. A ZigBee coordinator in the gateway constructed and maintained the ZigBee wireless local network. After initiating the smart gateway, local terminal nodes were detected and connected into the wireless network if the connection requests were approved. Based on the connection characteristics of the ad hoc network, entire coverage of a building can be achieved by a few gateways using the bridging functions on the ZigBee nodes. In the gateway, a wireless router module was utilised to realise the protocol conversion between the ZigBee local network and the Internet. The datasets were transmitted from the ZigBee coordinator to the router via a universal asynchronous receiver transmitter (UART). The router supported TCP/IP and an Ethernet interface for delivering datasets to the cloud server. The smart gateways gathered the electricity utilisation datasets from the smart metres using TCP/IP. The smart gateways not only received the connection requests but also responded to manual specifications transmitted from the cloud server. When a connection request was received by a gateway, the gateway established a communication link to realise reliable dataset transmission.

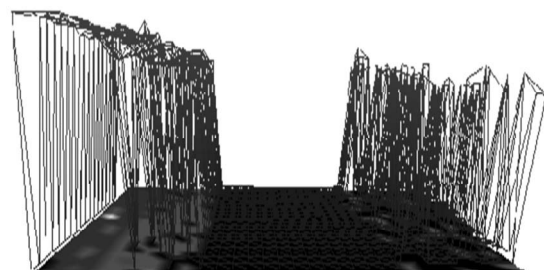


**Fig. 5.** The applied router and the smart gateway for connecting the air conditioners to the Internet.

The cloud server, which was considered an intermediary for delivering user instructions over the Internet, analysed the request type and responded with the relevant behaviours. The cloud server utilised a deep learning algorithm to analyse the environmental information and electricity consumption datasets to formulate a reliable solution to save energy.



(a)



(b)

**Fig. 6.** The visualisation results of the power consumption. (a) Visualisation on a mobile device and (b) visualisation on a PC.

In the mobile terminal, the real-time electricity consumption was displayed with several data visualisation methods to indicate the operational states of air conditioners, as shown in Fig. 6. With these visualisation results on mobile devices and PCs, users were encouraged to pay more attention to their electricity utilisation habits. In addition, the mobile terminal supported remote modification of the operational parameters of the air conditioners through the wireless network.

## 5.2 Analysis of the DBN Application

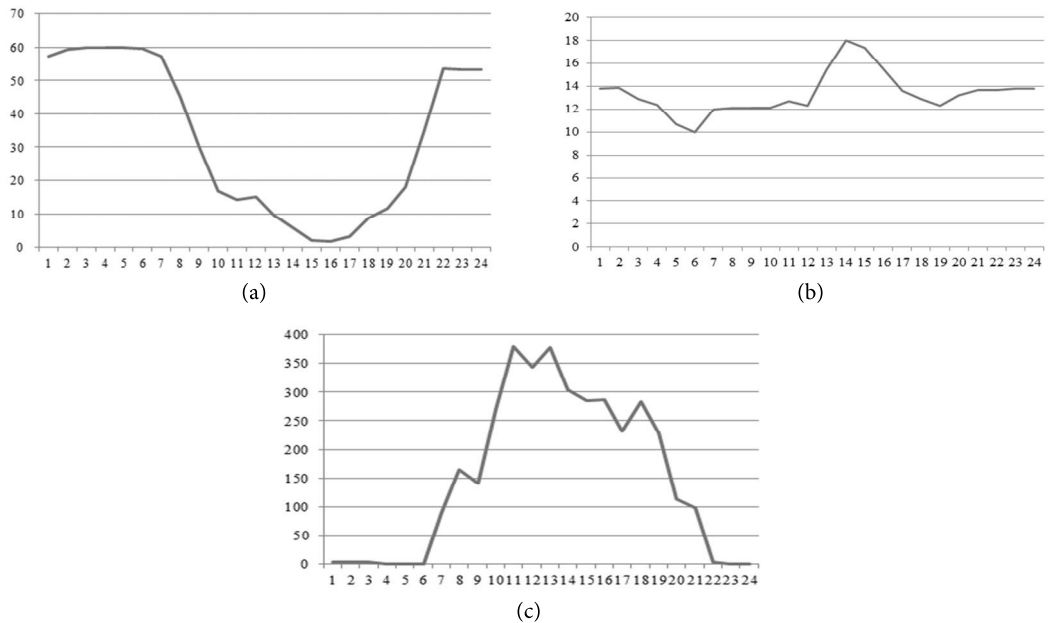
The electricity consumption datasets of air conditioners were collected from 77 different customers for 35 days, from July 1 to August 4, 2016. Since the peak periods of electricity consumption were distributed over several time intervals per day, we classified these datasets into separate groups according to the various electricity usage behaviours. The labelled datasets were trained using the DBN algorithm while the cloud server tested the unlabelled datasets using the DBN to estimate each user's type. Based on the electricity utilisation types, adaptive energy-saving solutions were suggested to the new customers. Meanwhile, the electricity consumption analysis results were provided to the supply side so that the power stations could allocate appropriate amounts of energy without extra waste.

In our experiments, the electricity consumption datasets collected from the metres were transmitted to the cloud server by the gateways. In the pre-training phase, 35 customers were divided into three groups: hotel, family and office. In the DBN training process, 100 sets in each group were randomly selected as training datasets to establish the network models. Another 100 items were selected as testing datasets to evaluate the prediction performances of the three models. The average electricity consumption distributions in the hotel, family and office groups over 24 hours are illustrated in Fig. 7(a)–(c), respectively. The x-axis represents 24 hours of a day, and the y-axis represents the electricity consumption in watts. The peak periods of air conditioners in the hotel group ranged from 6:00 to 19:00, while the usage in the family group was steady over the whole day. Since the datasets were collected in the summer, the electricity consumption reached its peak at noon to maintain the cool temperature for the majority of the family group. Meanwhile, the running periods of the air conditioners in the offices were concentrated from 9:00 AM to 7:00 PM.

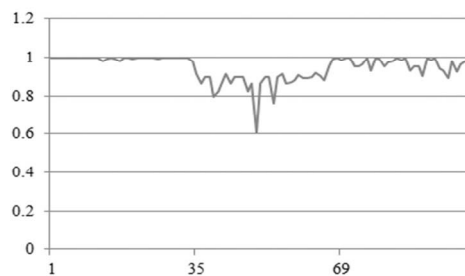
The DBN algorithm was implemented in a VC++ programming environment. In the pre-training phase of the DBN, the weight and bias parameters of every layer were initialised using electricity consumption as input and user labels as output. In our implementation, the learning efficiency was set to 1 and the number of training epochs was set to 500. After several rounds of training, the optimum training results were achieved when  $200 \times 200$  nodes were allocated in the hidden layers. After pre-training, the RBM parameters of each layer were initialised. Based on the input datasets and the loss function, the DBN was fine-tuned by adjusting the weights and biases of the multiple layers.

In the testing phase, 99 datasets were selected as testing samples, which were classified using the proposed DBN. Fig. 8 shows the accuracy results of label estimation, where the x- and y-axes represent the sample indices and accuracy, respectively. Testing datasets 0–33 were gathered from 34 air conditioners in hotel rooms; their average estimation accuracy was 0.9917. Since the electricity utilisation habits were similar in hotel rooms, the datasets were smooth and the extracted features were concentrated, so the testing results were significant. Testing datasets 34–66 were gathered from 33 household air conditioners. Since different families had different habits, the features of the new dataset did not completely match the extracted features, so the average estimation accuracy was approximately 0.8801. Testing datasets 67–96 were gathered from 30 air conditioners in office rooms, whose estimation accuracies were stable, with an average of 0.9769. By analysing the results, the cloud server

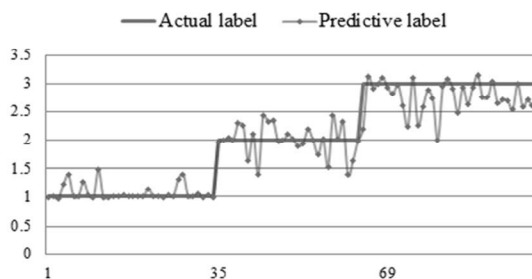
learns the users' habits and utilises this knowledge to formulate individual energy-saving solutions. We also implemented the extreme learning machine (ELM) in our datasets to compare the performances of the applied classifiers. As shown in Fig. 9, the average accuracy of the ELM prediction results was 0.88, which is less than that of DBN.



**Fig. 7.** The average electricity consumption distributions of the training datasets. (a) Hotel rooms, (b) family rooms, and (c) office rooms.



**Fig. 8.** The DBN testing results of the classification accuracies of electricity utilisation types.



**Fig. 9.** The prediction results using the ELM.

## 6. Conclusions

To refine customers' electricity habits, this paper proposed a smart IoT platform to analyse electricity utilisation features of air conditioners with a DBN algorithm. Using smart metres, the platform enabled a remote and automatic control function based on power consumption features and environmental information, including temperature and humidity. The metres also transmitted energy consumption datasets, along with the environmental information, to a cloud server through a ZigBee wireless network with smart gateways as the intermediate equipment. In the cloud server, a DBN algorithm was utilised to analyse the air conditioner usage habits to provide strategies for increasing the energy efficiency. In the future, the smart management of other appliances will be incorporated into this platform to promote energy conservation.

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