When Weather Matters: IoT-Based Electrical Load Forecasting for Smart Grid

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Liangzhi Li, *Student Member, IEEE,* Kaoru Ota, *Member, IEEE,* Mianxiong Dong, *Member, IEEE*

***Abstract*—Electrical load forecasting is still a challenging open problem due to the complex and variable influences, e.g. weather and time. Although, with the recent development of Internet of Things (IoT) and smart meter technology, people have obtained the ability to record relevant information on a large scale, traditional methods struggle in analyzing such complicated relationships for their limited abilities in handling non-linear data. In the paper, we introduce an IoT-based deep learning system to automatically extract features from the captured data, and ultimately, give an accurate estimation of future load value. One significant advantage of our method is the specially designed two-step forecasting scheme, which significantly improves the forecasting precision. Also, the proposed method is able to quantitatively analyze the influences of some major factors, which is of great guiding significance to select attribute combination and deploy on-board sensors for smart grids with vast area, variable climates and social conventions. Simulations demonstrate that our method outperforms some existing approaches, and can be well applied in various situations.**

***Index Terms*—Smart grid, Internet of things (IoT), load forecasting, metering infrastructure, big data.**

I. Introduction

Smart grid, as a power system for the future, has recently received lots of attentions. Although many encouraging research works have emerged in the relevant area, one grave problem remains unsolved, i.e., electrical load forecasting. An accurate estimation of future load variation is of great significance for competitive and deregulated electricity markets, where the load prediction is an important guidance, both for power companies and electricity consumers, to make decisions and operations [1].

The major obstacle in load forecasting is the numerous impact factors. There are so many possible influences that it is extremely difficult to find a meaningful relationship between load variation and these factors. In fact, even the acquisition of necessary data is not an easy case until quite recently. The emerging of smart meter infrastructures [2], efficient sensing methods [3], and Internet of Things (IoT) technologies [4] give us a chance, for the first time, to record and analyze possible influences on a large scale. With several equipped sensors, smart meters can be used to independently capture various environment data. Also, they can obtain the shared data from IoT-enabled devices. All these data will be uploaded to the central controller. Then a massive number of data can be accumulated for further analysis. However, it is still a challenging problem to handle the data, due to the complex and variable influences, especially the diverse weather conditions. Indeed, most existing time-series forecasting approaches [5] have some limitations when applied to electrical load prediction. The classical statistical methods are criticized for their limited abilities in handling non-linear data; and the computational intelligence methods are facing problems like inappropriate hand-crafted features, limited learning capacity, inadequate learning, inaccurate estimation, insufficient guiding significance, etc. Although there have been several attempts based on the state-of-the-art machine learning methods, which can partially resolve these problems, their performance can be significantly improved using some ingenious design introduced in the paper.

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To solve these problems, we desire to utilize the state-of-the-art deep learning methods [6] to automatically extract features from the historical data, and give an accurate estimation of future load value. For the sake of data collection, we implement an IoT-enabled system in an urban area of south China, as shown in Fig. 1. Smart meters are adopted to record and upload electrical and background data, with specially-designed sensors and IoT-enabled devices. They are deployed in every electricity consumption unit, and share their information with the control center. Ultimately, we obtain a large dataset in seven years from 2010 to 2016, including all conceivable factors. Then the data is used for the network training and influence analysis. As IoT and smart meters both have the ability of bidirectional communication, the recommendations and decision made by the control center can be sent to the demand side. The IoT infrastructure in Fig. 1 is an important part of the proposed system. The smart meters can connect to all the IoT-enabled sensors, gadgets and appliances in the electricity unit, for example, the smart homes. The proposed system can deal with all these data, and based on that, perform accurate load forecasting.

The main contributions of our work include:

- We propose an IoT-enabled load forecasting system based on the state-of-the-art deep learning technologies. Compared to the traditional time-series analysis methods, the proposed method can perform accurate prediction without hand-crafted features.
- We design an ingenious two-step forecasting scheme, which forecasts the daily total consumption at first, and based on that, predict the intra-day load variation. This method can significantly improve the forecasting precision, which is demonstrated in the experiment section.
- We work out an analysis method of possible influence

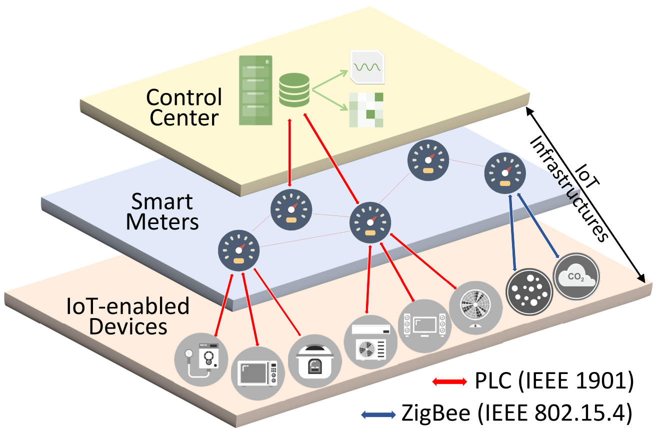


Fig. 1. The load forecasting and analysis system based on IoT-enabled sensors and devices.

factors. To our best knowledge, this is the first attempt to gain insight into the relationship between the factors and the actual load, which, we believe, will play a tremendous role in selecting attribute combination and deploying smart meters, especially for the smart grids in some countries with vast territory and varied climates.

II. Recent Advances in Load Forecasting

A. IoT-enabled Smart Meter Systems

Smart meter is a modernized electrical device that records the energy consumption and uploads it to the utility for billing and further analysis. The most cutting-edge smart meters not only have a two-way communication ability, but are equipped with real-time sensors which can gather the data of relevant factors. This kind of electricity meter is a vital part of advanced metering infrastructure (AMI), a system keeping the whole smart grid connected and informed. With AMI, the utility can obtain necessary data from the client-side, and push notifications and recommendations to the clients. Connected smart meter is a fundamental component for the future smart grid, and also a cornerstone of our research. Many researchers are working on this area [7].

IoT, as a hot topic in recent years, is a good approach to implement connected AMI systems. However, like any other applications using IoT technologies, the underlying network to connect smart meters must be carefully investigated. Some researchers find it necessary to clarify the exact capacities of existing wireless networks for the upcoming smart metering traffic [8]. A few preliminary conclusions have been drawn, including decreasing the communication interval and equipping phasor measurement units (PMUs).

In addition, an efficient distributed communication architecture has been proposed for the connection of smart meters [9], which can leverage data processing locally. Besides, with a carefully selected control centers [10], the cost of deployment and communication can be significantly decreased.

B. Time-series Forecasting Methods

Although time-series forecasting is a topic with a long history, it is still an open problem due to its complexity. The existing approaches are of two main types, namely, statistical methods and computational intelligence methods.

The statistical method is an obvious and natural solution when dealing with a series of numbers, including many algorithms with different design principles [11]. There is a famous exponential smoothing method called Holt-Winters (HW). HW is a good choice when the time-series shows both trend and seasonality. Two sub-models are included in HW, i.e., additive model for data with additive seasonality, and multiplicative model for data with multiplicative seasonality.

Although many classical statistical methods have emerged over the past few decades, they are currently disfavored due to their limited abilities in handling complicated nonlinear relationships. Computational intelligence, one of the hottest topic in current academia, becomes a key technology to accurately analyze and forecast time-series data. And, among all these computational intelligence methods, deep learning is in evidence [12]. Deep learning is a newly developed and fast-growing class of machine learning algorithms. A deep network has multiple hidden layers between input and output layers, in order to model complicated non-linear relationships. With enough training materials, which usually are labeled data, the parameters in a deep network can be well trained to extract complex features from large data. Therefore, deep learning methods have been successfully applied in lots of fields, including scene understanding, natural language processing, self-driving, audio recognition, etc. Because of its strong automatic feature extraction and pattern recognition ability, deep learning based methods are extremely suitable for electrical load forecasting, where lots of influences exist. The most similar approach with our proposed method is short-term deep neural network (SDNN) model [13]. This model contains three steps, i.e., data preprocessing, network training and forecasting. The historical weather conditions and load values are used as the network input. Compared to the aforementioned deep learning based approaches, our method adopts a specially designed two-step forecasting scheme, and takes into account various influences to analyze their impact.

III. Forecasting System: Concept and Design

When starting with the research of electrical load, we wonder what on earth are the possible influences. And which factors do have a role in the load variation? We decide to begin with the analysis of historical record, and try to find some inspirations. Fig. 2 presents an electrical load record of a large city in south China. The data is sampled every five minutes, from January 2014 to June 2016. As can be seen, there are some obvious patterns in the load variation. On one hand, these records reflect an annual periodicity. The power load peaks between June and October every year, and hits bottom around February, which has significant seasonal characteristics. On the other hand, there is also an obvious daily periodicity, i.e., the load value keeps high in the daytime, and drastically drops down at night.

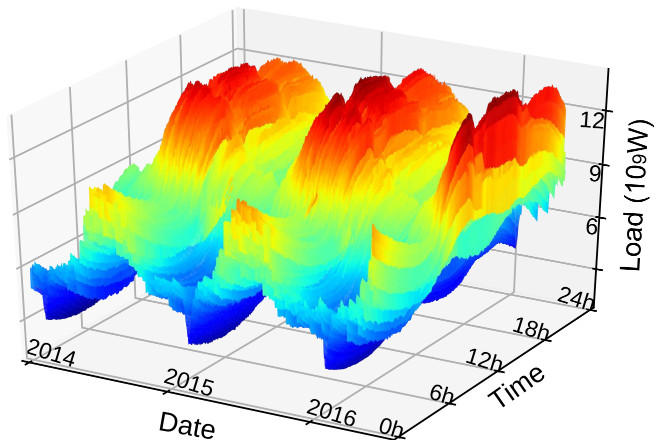


Fig. 2. Urban electrical load in China (sampled every five minutes).

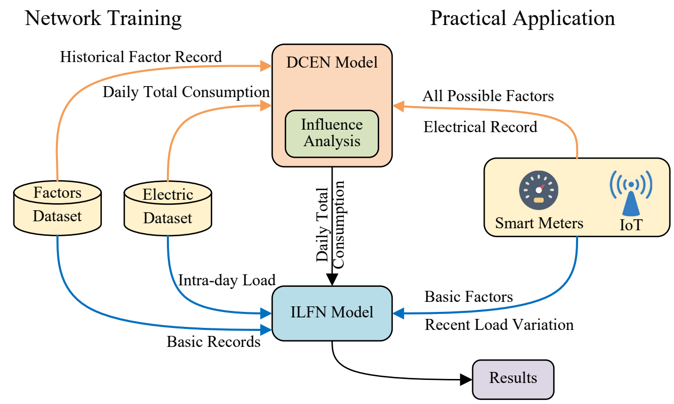


Fig. 3. The framework of the proposed load forecasting system.

Although with some simple data analysis like this, the presented load patterns can lead to a few preliminary conclusions, it is very difficult to truly understand the complex relationship between the power consumption and influence factors. In fact, weather and some other factors play much more parts in electrical load variation, and also in more complicated ways, which is far beyond the capacity of humanity and traditional load forecasting methods. Besides, we empower the smart meters with the ability to communicate with other IoT-enabled devices in the system, leading to more extensive input attributes. As shown in Fig. 1, the IoT infrastructure is a fundamental component, because it monitors the factors and sends the data to the control center. The IoT infrastructure consists of the IoT-enabled devices, including the smart meters, gadgets and appliances, and the communication network. For economy and reliable communication, we adopt Power Line Communication (PLC), which can transfer low bit-rate data with low costs [14], and ZigBee, which can exchange data wirelessly within a 100m range such as in a home or building, as the communication network. And smart meters, just as the sink nodes in the wireless sensor network (WSN), are responsible for collecting data from the household devices and sensors, and uploading the data to the control center every 30 seconds. The captured data is extremely complicated and contains lots of useful information. We desire to learn these patterns with a deep learning based system to give out an accurate estimation of the future electrical load.

As mentioned above, we notice that several researchers have attempted to utilize deep learning in load forecasting, but many of them are facing a problem of low precision. Frequently, the existing approaches give inaccurate daily consumptions even when they have the ability to predict short-term load precisely. It is a serious problem because many participants of electricity markets regard the *daily* consumption value as an important reference for decision-making. A too large estimation may lead to energy waste, while a too small value can possibly cause an insufficient supply. We adopt a specially designed two-step forecasting scheme to address this problem.

The framework of the proposed load forecasting system is presented in Fig. 3. In our method, two individual models are used to respectively predict the daily consumption and intra-day variation, i.e., daily consumption estimation network (DCEN) and intra-day load forecasting network (ILFN). There are two major reasons that we design the two-step forecasting scheme. One reason is, the estimation value of DCEN is not only a helpful guidance for electrical companies and consumers, but an important input to ILFN model, which takes the daily consumption value as a reference and also a limitation. Therefore, with the proposed scheme, the estimated variation can be much closer to the actual load values. The other reason is that electrical load is influenced by various factors, which is usually in unit of days, such as the daily maximum or minimum temperature, daily precipitation, daily sunshine duration and, of course, the date. And, the relevant data is also most often obtained in the unit of days. Based on these facts, we concentrate all the possible factors at the DCEN model to accurately predict the daily consumption, and only adopt several basic factors to support the intra-day forecasting, in order to simplify the network structure,

There are ten hidden layers in the proposed DCEN model. Layer one and layer two each has 4096 neurons, layer $3\sim5$ each has 2048 neurons, and layer $6\sim10$ each has 1024 neurons. We envisaged implementing DCEN as an extremely complicated model to hold and analyze the super large data. However, we found that the data engineering is a more efficient way for this task. With well-selected input, even a common deep model can extract sufficient features and give meaningful information for the load forecasting. We will demonstrate this in the experiment section.

As mentioned above, the key problem in DCEN model is the selection and preprocessing of the input data. A massive number of data is acquired by the proposed IoT system. Among them, we pick the following data as the input. As the most instructive reference, the daily consumption of past 7 days is selected; to reflect any periodic characteristics, the time relevant attributes are also adopted, including the date, the Chinese lunar date, day of the week; as the most important and complicated data, weather relevant attributes are of great significance to the DCEN model, including the temperature, air pressure, vapor pressure, precipitation, evaporation, wind

TABLE I
FEATURES COMPARISON OF FORECASTING SYSTEMS.

	Existing systems	IoT-enabled system
Data source	On-board sensors	IoT devices
Granularity	Community	House / Room
Data scope	Limited sensors	Extended by devices
Controllability	Controlled by provider	Controlled by residents
Deploy cost	Expensive sensors	Low-cost sharing
Adaptability	Fully applicable	Available in IoT network

speed and sunshine duration. These data are preprocessed to give out the maximum, minimum and average values, and then normalized to generate the final inputs, which include 7 electrical attributes, 3 time relevant attributes and 22 weather relevant attributes.

After obtaining the daily consumption data, we adopt ILFN model to estimate the intra-day load variations. ILFN is also a classic deep model with five hidden layers. And each layer has 512 neurons. The difference is that ILFN needs fewer input attributes, compared to DCEN model, because all the possible influences have been handled by DCEN, and most of them can be neglected in ILFN. The input only includes several basic factors and the recent load variation. In detail, the input data includes the estimated daily consumption value, the time relevant attributes, the load values in the last five time units and some relevant readings. DCEN and ILFN are performed for each electrical consumption unit for more nuanced and accurate forecasting. This is mainly benefited by the lower-granularity data from IoT-enabled system. Table I gives the comparison between traditional systems and the IoT-based system. It can be seen that, the proposed system is able to monitor the detail information of the residents' house, and give solid data support for the forecasting system. These valuable data can be a useful addition to the records captured by the on-board sensors, such as the operation log of smart appliances, which can be important reference for the residents' energy usage habits. As one of the most important factor, some detailed weather condition data can only be captured by the households sensors, such as the indoor temperature, sunshine duration and indoor air quality, which differentiate in every house but have a strong effect on the energy consumption.

IV. INFLUENCE ANALYSIS

We need to go a step further than merely implementing a forecasting system. Although the proposed DCEN and ILFN model can make accurate predictions, it is no doubt necessary to figure out the mechanism behind the network structure, rather than simply leaving it as a black box. We start with clarifying the focus of the system, in other words, what the system really concerns among all the input attributes, including the historical load, weather factors, and time relevant information. This is very important not only for this research, but for other load forecasting applications in different area, because the analysis of forecasting mechanism can serve as a useful guidance for system design. For example, the 32 attributes we select in the proposed instance are probably not suitable for other smart grids, especially the Chinese lunar date, which is only of significance to some area in China. So how to find the "right" attributes for a specific area? Influence analysis is an efficient way to perform this task. In the stage of system design, researchers can push all the possible factors into a prototype system, and after adequate training, analyze the contributions of each attribute. Ultimately, the researchers are able to obtain the accurate combination of possible factors. It is an economy solution to know the factors that truly matters before the large-scale deployment of smart meters and sensors. Besides, following the trend of IoT, an increasing number of devices will be IoT-enabled. Therefore, the smart meters will get much more complicated input data in the future, and the influence analysis will play a key role in discriminating the value of various data source. In addition, influence analysis can also be used as a technical measure for the network overfitting, which is a common and serious problem in the training process, but with few effective measuring means for a long time. Overfitting frequently occurs when the deep model is too complicated while having insufficient input data. An overfitted model may have good statistical results on the training materials, but usually perform poorly on actual applications, due to its overreacts to the minor fluctuations. Through influence analysis, researchers can obtain some information regarding whether the overfitting occurs or not. It is mainly because that, an overfitted network usually extracts meaningless features from the raw data, which are impossible to comprehend in most cases. On the contrary, well-trained networks analyze the data in a human-like way. This difference can become an effective standard of distinguishing the overfitted networks from normal ones.

For these purposes, we design a novel visualization method to analyze the contributions from each input attribute to the final output. We notice, a trained network have fixed parameters, including weights and biases. Therefore, the final output is merely related to the input. And if we change one input unit of an input attribute, the output result will also be changed, which gives a way to infer the contribution of one single input attribute. The analysis algorithm is explained below. First, each attribute in each input sample is fine-tuned to generate new output results. Then each new output value is compared with the former results to show their own contributions. At last, the normalized differences are presented in heatmap form.

An example of the proposed influence analysis is shown in Fig. 4. The analysis is conducted with a well-trained network. For simplicity, only some relevant attributes, which have significant influence on the final forecasting result are presented in the figure, including the date, the Chinese lunar calendar date, the day of the week, the temperature and the air pressure. The influences are shown in color. And the red areas have bigger influences than the blue areas. Since all the attributes are normalized and get changed at a same extent, the generated heatmap can give an intuitive representation regarding which parts of the attributes give the most influence to the forecasting results.

Among all the presented heatmaps, the temperature attribute

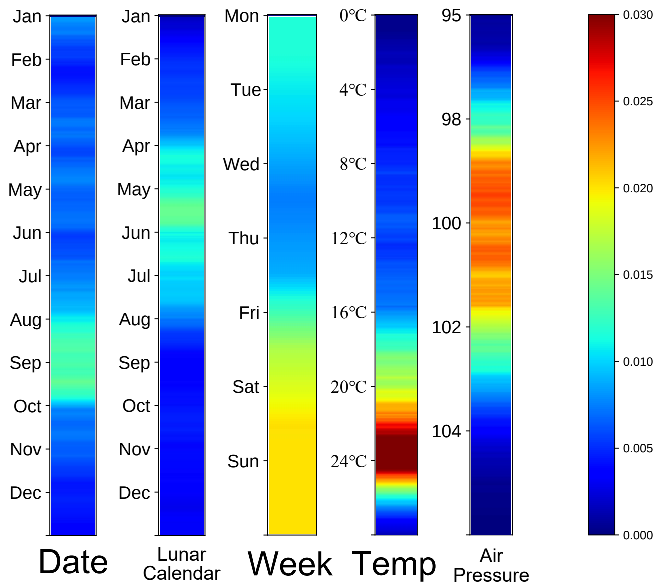


Fig. 4. The generated heatmap for influence analysis.

has the most significant effect on the final output, according to the highlighted zone around 25 Celsius degree in the temperature channel. As can be seen, the highlighted zone is converged around 25 degree, which is mainly because 25 degree is a sensitive cut-off point to determine whether to use the air conditioner. When the temperature is lower than 25 degree, there is no cooling needs. On the other hand, when the temperature is much higher than 25 degree, the cooling needs always exist, and a minor temperature change has little influence on the power consumption. Traditionally, there is no demand for heating in south China. Therefore, low temperature also has little influence on the electrical load. We are very surprised at the rationality and interpretability when we see the visualization results for the first time. And, not only the temperature but other attributes show meaningful heatmaps. For example, the date channel and lunar date channel both have highlighted zones around several legal holidays, when the factories are usually closed and, as a result, the electrical load drops down. Lunar date is a traditional calendar in China, and many holidays are based on lunar date. Therefore, we set the attribute of lunar date to reflect some specific periodical patterns in China. In the week channel, the influence value of weekends is higher than the one of weekdays, because the weekends are also rest days for many industries. As for the air pressure, according to several existing research, there is a strong inverse correlation between the air pressure value and electrical load. It is because that the lower air pressure frequently results in the oppressive weather, which fuels the increase in cooling needs. Besides the channels presented in the figure, we also analyze the influence of historical load data, i.e., the daily consumption of past 7 days. Their normalized influence values are 0.07, 0.011, 0.009, 0.007, 0.005, 0.008 and 0.007, respectively for the past days from yesterday to 7 days ago. It can be seen, the closest point in time has the most significant effect on the forecasting result.

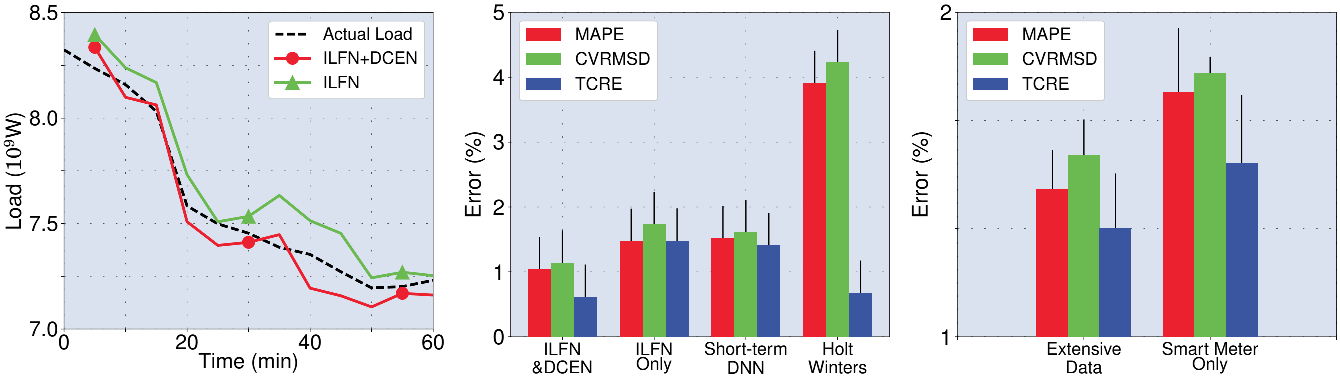
As expected, the visualization results demonstrate that, the proposed system can draw rational conclusions with intelligible inferential process. The analysis method enables researchers to select attribute combinations and judge overfitting networks.

V. Performance Evaluation

To show the actual forecasting performance of our method and demonstrate the effectiveness of the specially designed two-step forecasting scheme, several simulations are conducted in this section. The input is the actual record of an urban area in China. We create an instance [15] of the proposed models, and train the system with the input data. As shown in Fig. 5(a), we perform two forecasting tests in a period of one hour. The red line indicates the forecasting results which are generated with both of the proposed DCEN and ILFN models, the green line represents the results generated with only ILFN model, and the dotted line is the actual load value. It can be seen that, although both forecasting lines are close to the truth value, the green line shows some offset as a whole, when the two-step forecasting is not adopted. More precisely, nearly all prediction values in the green line are bigger than the actual value, leading to an inaccurate daily total consumption, which is much bigger than the truth value. In contrary, the red line is well distributed in both sides of the dotted line, which may result in a more accurate total consumption. A quantitative analysis experiment is performed to give a precise performance comparison between these two tests, also with another two existing approaches, i.e. the state-of-the-art deep learning based SDNN model [13] working on the same 32 attributes including electrical data, time relevant data and weather data, and the classical HW method working with merely electrical record.

We adopt three mathematical indexes to quantitatively measure their performance. Fig. 5(b) gives the comparison result. The mean absolute percentage error (MAPE) is a famous measure of forecasting precision in statistics. MAPE is scale-independent, and is favored when compare predict accuracy between different datasets. The root mean square deviation (RMSD) is another accuracy index, but can only be used to compare prediction errors of different models for a same dataset, as it is scale-dependent. RMSD is normalized with the mean value of the measurements in the paper, namely, coefficient of variation of the RMSD (cvRMSD). In addition, we design a new measure named total consumption relative error (TCRE) to show the effect of our two-step forecasting scheme. TCRE is calculated using the actual daily consumption value and the sum of all estimations in one day. All of these three measures express as percentages.

In Fig. 5(b), the first group represents the result of the proposed two-step approach, the second group indicates the prediction without DCEN model, the third group is the SDNN model, and the last group represents the HW method. As can be seen, even without DCEN, the proposed method can achieve a state-of-the-art performance similar to SDNN. However, it is significantly outperformed by the proposed two-step approach in the measure of TCRE. These numerical results once again demonstrate the necessity and effectiveness of our



(a) (b) (c)

Fig. 5. Evaluation results of the forecasting methods. (a) Forecasting results (12 predictions in 60 minutes). (b) Comparison of forecasting precision. (c) Comparison in an IoT-enable building.

two-step forecasting method. Compared to other approaches, the proposed method performs much better in the prediction precision of both intra-day load variation and daily total consumption.

To demonstrate the effect of the extensive data from IoT-enabled devices, we perform an additional comparison experiment in a residential building in the same city. As shown in Fig. 5(c), the first group is the results of the proposed method using lower-granularity data, which is monitored per house; while the second group represents the results using higher-granularity data, which is captured as the whole building. We can see the first group outperforms the second one in all of the three indexes. This improvement can be attributed to the differences of temperature, humidity, sunshine duration, indoor air quality among the rooms in the building. Through IoT-enabled devices, the system obtains the ability to accurately forecast the energy consumption for every electrical unit, and as a result, improve its prediction precision of the total consumption.

VI. Conclusion

An IoT-based electrical load forecasting method is proposed in the paper. A huge advantage of the method is its two-step forecasting scheme, which significantly increases the prediction precision for daily total consumption. Another major difference is that, we adopt deep learning methods to learn complicated patterns form all the possible influences, and achieve a state-of-the-art forecasting performance in the evaluations. In addition, we also propose an analysis method to find the relationship between the influences and the electrical load, and design a heatmap generation method to show the specific impacts of each attribute on forecasting results. This analysis method is also of much guiding significance for the smart grids in other countries, especially for the ones with vast territory and varied climates. The results prove its effectiveness.

One limitation is that, in the proposed system, a huge number of data needs to be transferred on the communication network, which can bring a big challenge to the existing infrastructures. One feasible solution is to adopt edge servers near the client side for better computing balance and less communication cost, which is also included in our future works.

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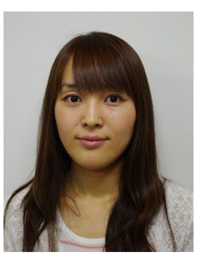

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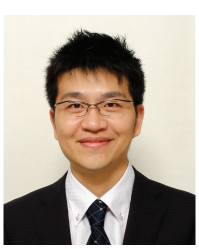

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