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Spatial granularity analysis on electricity consumption prediction using LSTM recurrent neural network

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Abstract

The building sector takes a large proportion of electricity consumption and carbon emission in high-density urban areas. To reduce the carbon emissions and use energy more efficiently in the building sector, home energy management system (HEMS) is proposed and used. In the HEMS, the prediction of electricity consumption in the short-term future is used to support the decision makings in the HEMS. Although there existed a number of studies in the prediction of electricity consumption in buildings, there lacks a spatial analysis in the prediction performance, especially on the appliance or sub-meter level and household level. The authors made an assumption that by the performance of household energy consumption prediction can be significantly improved if the prediction is aggregated from the prediction data at the appliance or sub-meter level. Next, two typical datasets are used to validate the assumption by comparing the prediction performance of aggregating the prediction data at appliance level and the one of making direct prediction at the household level. The models used for the prediction are standard stateful long short-term memory (LSTM) neural networks, which have been proofed to be promising in load prediction by previous studies. The results from the comparison validated the assumption, showing that the prediction performance can be significantly improved if prediction is made at the appliance-level first and then aggregated to get the household-level prediction. Therefore, the authors conclude that prediction at the finer appliance granularity level can significantly improve the performance of household-level electricity prediction.

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Keywords: electricity consumption prediction, LSTM model, appliance level, submeter level, household level, spatial granularity analysis

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1. Introduction

With the growth of population and the improvement in the human living level, buildings become one of the dominant sectors of energy consumption and carbon emissions. Electricity is one of the primary forms of energy consumed in buildings. Studies show that more than 38% of primary energy and 76% of electricity are consumed in buildings in the United States in 2015[1]. Therefore, how to use the electricity more efficiently in buildings is critical to reducing the building energy consumption. The home energy management system is considered an effective way. Predicting the electricity demand in the buildings accurately in the short-term future serves as the intelligent decision-making tool for energy management system.

The prediction can be conducted at different levels, for example, the sub-transformer level, the community level, the building level, and household level. As the prediction level becomes finer, the randomness and uncertainties induced by human behaviors or the weather variability become more apparent and it is usually tough to handle that randomness and uncertainties, which make the electricity demand prediction at the building or household level inaccurate. In modern buildings, it is more common to install smart sub-meters for the major appliances such as HVAC system. In addition, the research in non-intrusive load monitoring (NILM) makes it possible to acquire the appliance-level load curves in a household/building without installing the expensive sub-meters. Therefore, the historical data of appliance-level energy consumption is easily accessible, providing the opportunities for the electricity consumption prediction at finer details in the buildings. The appliance-level electricity consumption prediction can benefit the building energy saving in different ways. On the one hand, energy saving plans for the building occupants can be generated if they know the detailed energy consumption data of the appliances. For example, with such information, the utility provider could inform the consumers a better demand scheduling and allocation plan for appliance usage. On the other hand, it can benefit the adoption of renewable energy systems in the buildings. The finer electricity demand prediction helps to determine the size of the home renewable energy system, encouraging the occupants to take an active role in electricity market by selling the surplus electricity to the grid utility. Besides, it can provide property owners with a more comprehensive understanding of the spatial distribution of energy consumption in the buildings or houses.

This paper aims to compare and analyze the accuracy of the household electricity consumption prediction of the same model conducted at different spatial granularity levels: the household level and the appliance/submeter level. LSTM recurrent neural networks are used as the prediction models, and two case studies are conducted to compare the prediction accuracy of the total electricity consumption at the household level. The remainder of this paper is organized as follows. Section 2 introduces the related work in electrical demand prediction and identifies the research gap. Section 3 describes the methodology including the model and the application to demand prediction field. Section 4 presents the results of the proposed assumption validation. Section 5 concludes the paper and envisions the future work.

2. Literature review

The existing studies on electricity consumption prediction can be divided into two categories based on the approach adopted: statistical methods and artificial intelligence methods.

Schmidt et al. [2] presented a probabilistic model for electricity usage prediction of appliance based on the historical data by considering three major factors: 1) the elapsed time since the appliance was last used; 2) the time of day when the appliance was probability used; 3) the occupant's behavior pattern (for example, people may use the washing machine during the weekend twice or triple than working days). The authors aim to provide recommendations to the occupants and improve home automation system for load shifting or scheduling without scarifying the occupants' comfort. However, the authors only make on-off predictions without considering the energy consumption level. Similarly, Shailendra et al. [3] used the Bayesian network based prediction model for predicting the multiple appliance usages and energy consumption by utilizing the two kinds of probabilistic associations: appliance-time, appliances-appliances. Shailendra et al. claimed that the proposed method outperformed other models including Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) at each stage and achieved high accuracy in the energy consumption prediction in both short-term and long-term.

Deep learning methods are proved to outperform the traditional prediction models like radial basis function neural networks (RBFNN), Multiple Linear Regression (MLR), and Support Vector Regression (SVR). Li et al. [4] combined the stacked autoencoders (SAEs) with the extreme learning machine (ELM) to predict the electricity consumption at the building level and achieved a high accuracy. The proposed method significantly outperformed other four prediction models: Backpropagation neural networks (BPNN), SVR, Granular RBFNN and MLR. However, Li et al. only considered it as a one-step prediction problem based on half-hour and hour data. This is not practical because it is less useful to predict the energy demand in the next hour than to predict the energy demand in the next 24 hours. In contrast, multi-step prediction can meet the practical requirement and have the advantage of preserving the temporal statistical dependency in the forecasted time series [5]. Instead, Kong et al. [6] made predictions under multiple scenarios with different time horizons using the LSTM model and compared it with other models including BPNN, k-nearest neighbors algorithm (KNN), and ELM. Kong et al. addressed this problem at the substation and household level and compared the prediction performance of two cases: aggregating the individual load prediction and predicting the aggregate load at the substation level. The result shows that, by aggregating the individual load prediction data, the performance improved by 0.49% and 1.08% for LSTM and BPNN-T models, respectively. Zheng et al. [5] also explored the application of LSTM in time series prediction and compared its performance with other methods using two datasets: one international airline passenger dataset and one extended electricity consumption dataset. The result shows the promising advantages of LSTM approach in the challenging short-term electric load forecasting field.

However, most of the prediction approaches are conducted at the system or substation levels [5,6]. Some of them are conducted at the building or household level [4,7]. Few of them are conducted at the appliance level [2]. To the authors' best knowledge, these different prediction levels have not been well studied and compared. To deal with this research gap, experiments should be conducted to reveal the impact of spatial granularity on the prediction models' performance. Jain et al. [8] also investigated the impact of spatial monitoring granularity on prediction accuracy. They used the sensor-based single-step energy prediction model to make a prediction for a multi-family building in New York City. They concluded that the optimal monitoring granularity occurs at the *by floor* level. However, the prediction is only conducted by a single step, and the spatial impact is only analyzed by the building, floor and unit levels, without going into the appliance level in one unit or family. Besides, they used the coefficient of variation (CV) and revised CV as a performance metric, which is not commonly used in load prediction community. In this paper, mean absolute error (MAE), mean relative error (MRE), symmetric absolute percentage error (SMAPE), and root mean squared error (RMSE) will be used as evaluation metrics to compare the observed values and the predicted ones. Moreover, different models are used. In this paper, the authors use the LSTM model. It makes sense to explore the impact of spatial granularity on different models.

Instead of proposing a brand-new prediction model to acquire higher prediction accuracy than other models, this paper aims to analyze the impact of spatial granularity over the prediction accuracy. Therefore, the experiments in this paper are conducted using the standard stateful LSTM models without fine tuning but keeping the same neural network parameters. Some information, such as the local weather data, is ignored.

3. Methodology

3.1. Long-Short Term Memory(LSTM) recurrent neural network model

Recurrent neural network (RNN) is one type of neural networks with internal loops. The most prominent characteristic is that RNN can recognize the temporal structures of the input data, making RNN best suited for time series data mining. Electricity consumption prediction is a typical time series prediction problem relying on time dependency patterns. Therefore, RNN is considered an appropriate data-driven approach for energy consumption prediction. However, a major drawback of the classical RNN approach is that they cannot learn the long-term temporal structures effectively because of the vanishing or exploding gradient problem when updating network weights.

LSTM recurrent neural network is one special RNN proposed to tackle the vanishing or exploding gradient problem. Like classical RNN, LSTM neural network also has self-connection so that the information at the previous time steps can be reflected in the output of next timestep. The difference is that the LSTM neural network introduces more complicated units in the hidden layers: an input gate *i*, a forget gate *f*, an output gate *o* and a memory cell *c* (internal state). These revolutions make LSTM have the ability to remove or add specific information to the internal state by controlling the update of the memory cell. The structure of a standard LSTM neural network is shown in Figure 1.

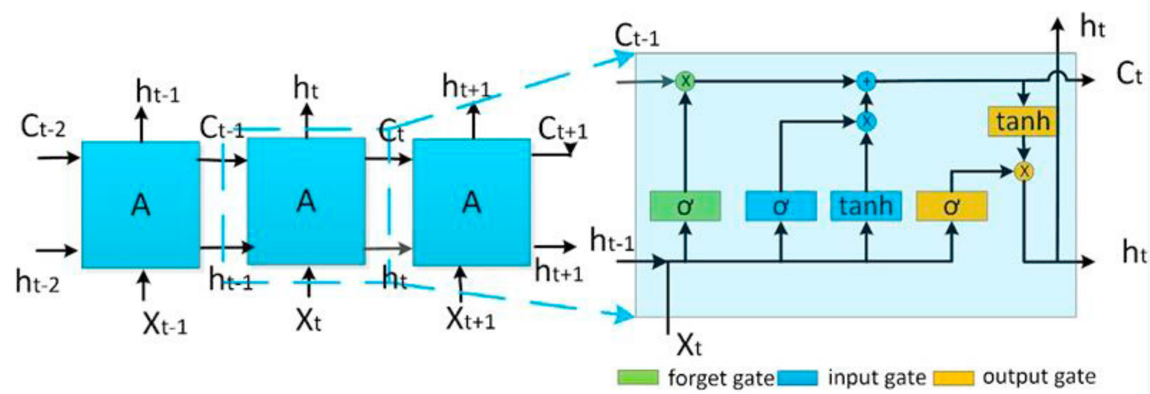

Figure 1. The unfolded standard LSTM recurrent network ('A' denotes a complicated layer comprised of a forget gate, an input gate, an output gate and a memory cell)

3.2. Electricity consumption prediction with LSTM model

The implementation of standard LSTM prediction model is conducted under the *keras* framework with *Tensorflow* as the backend using *Python* language. The prediction only used the historical electricity consumption data and the datetime as the features to predict the electricity consumption in the next few timesteps. In addition, *public holiday or not* is used as another feature, denoted by a binary value. Two case studies are analyzed for different time horizons. Case Ⅰ is used to predict electricity consumption in the next 24 hours with the historical data in the last 240 hours, while case Ⅱ is used to predict electricity consumption in the next seven days with the historical data of the last 70 days.

Since the appliance-level prediction model is not accurate enough for all types of appliances and this paper does not develop an accurate prediction model for a single appliance, synthetic household-level data or synthetic appliance-level data are constructed by adding up the consumption data of several appliances together. The household-level and appliance-level data are both modeled using the same standard stateful LSTM model. The standard LSTM model comprises two LSTM layers and a dense neural network. '*adam*' optimization method is adopted, and 'MAE' is used as loss function.

To compare the prediction performance at the household level and appliance or submeter level, several widely adopted metrics are used, including the SMAPE, MRE, MAE, and RMSE, as defined in equation (1) to (4).

$$\mathrm{SMAPE}=\begin{cases}\dfrac{200\%}{N}\sum_{t=1}^{N}\dfrac{|y_t-\hat{y}_t|}{|y_t|+|\hat{y}_t|} & \text{if } |y_t|+|\hat{y}_t|\neq 0\\ 0 & \text{if } |y_t|+|\hat{y}_t|=0\end{cases} \tag{1}$$

$$\mathrm{MRE}=\frac{1}{N}\sum_{t=1}^{N}\frac{|y_t-\hat{y}_t|}{y_t} \tag{2}$$

$$MAE=\frac{1}{N}\sum_{t=1}^{N}|y_t-\hat{y}_t| \tag{3}$$

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{t=1}^{N}(y_t-\hat{y}_t)^2}{N}} \tag{4}$$

4. Result and discussion

In this section, two public datasets are analyzed to validate the assumption that predicting the load consumptions at finer granularity level will improve the performance of predicting the total household electricity consumption. Two situations are compared for each dataset using the metrics above: one is to aggregate all the appliances or submeters energy consumption data and then conducts the household-level prediction, another one is to predict the energy consumption of each appliance or sub-meter individually and the aggregate the predicted data together to get the household-level prediction.

4.1. Case study Ⅰ: NZERTF dataset

Net-Zero Energy Residential Test Facility (NZERTF) [9] is a single-family house testbed on the campus of the National Institute of Standards of Technology in Gaithersburg, U.S. The collected dataset covers the period from February 1, 2015 through January 31, 2016, containing 63 appliances in total. The electricity consumption of all the 63 appliances is predicted using the same stateful LSTM model. The past 240 hours' historical consumption data are used as the input and the next 24 hours energy consumption are predicted by the models. Those appliances with high accuracy in energy consumption are selected to construct the synthetic house level aggregated data. Therefore, 49 appliances are selected to construct the aggregate house level data whose SMAPE values are less than 0.1. The comparison of two situations is summarized in Table 1.

Table 1. Prediction performance at two different prediction granularity level: appliance level and synthetic house level.

Metrics	Forecast the aggregated (house level)	Aggregate the forecasts (appliance level)
SMAPE(dimensionless)	0.103	0.044
MAE(Wh)	245.4	124.4
MRE(dimensionless)	0.086	0.048
RMSE(Wh)	320.9	189.2

Instead of constructing the synthetic house level consumption data, a synthetic appliance is generated by adding together the remaining 14 appliances whose SMAPE values are larger than 0.1. The comparison of two situations is summarized in Table 2.

Table 2. Prediction performance at two different prediction granularity level: synthetic appliance level and real house level.

Metrics	Forecast the aggregated (house level)	Aggregate the forecasts (synthetic appliance level)
SMAPE(dimensionless)	0.386	0.214
MAE(Wh)	4157.2	3798.5
MRE(dimensionless)	0.358	0.392
RMSE(Wh)	5489.6	5176

4.2. Case study Ⅱ: UCI household dataset

The University of California, Irvine (UCI) released the individual household electric power consumption dataset on UCI machine learning repository [10]. This dataset measured the electrical energy consumption in a household with the sampling rate of 1/60Hz for four years. Four meters are installed in this house: three sub-meters and one household-level meter. Similarly, two situations are predicted using the precisely same stateful LSTM model. One synthetic sub-meter data is generated by subtracting the readings from the other three sub-meters from the one of the household-level meter. The past 70 days' historical data are used as input, and the next seven days electricity consumption is forecasted by the models. The performance comparison is summarized in Table 3.

Table 3. Prediction performance at two different prediction granularity level: sub-meter level and real house level.

Metrics	Sub-meter 1	Sub-meter 2	Sub-meter 3	synthetic sub-meter 4	Forecast the aggregated (house level)	Aggregate the forecasts (sub-meter level)
SMAPE(dimensionless)	0.743	0.716	0.228	0.181	0.19	0.174
MAE(Wh)	807.2	1177.3	1996	2102.7	4386.2	4063.7
MRE(dimensionless)	1.186	1.66	0.914	0.49	0.581	0.61
RMSE(Wh)	1066.4	1715.3	2590.4	2757.5	5663.2	5294.6

As illustrated in Table 1-3, the prediction performance of the household-level electricity consumption can be significantly improved when the prediction is conducted at the appliance-level first and then aggregated to get the household-level prediction. In Table 3, it is observed that the prediction performance in terms of sub-meter 1 and sub-meter 2 is not so accurate. However, when adding the predictions of the four sub-meters together, the performance of the household-level prediction is improved. It is expected that when predicting the load consumption of sub-meter 1 and sub-meter 2 more accurately, the second situation: *aggregating the forecasts* will outperform the first situation more apparently.

5. Conclusion and future work

In this paper, the authors used the LSTM neural network to build a multi-step load prediction model. The spatial impact on the household electricity consumption prediction's accuracy is analyzed. An assumption is made that predicting the electricity consumptions at the finer appliance or submeter granularity level will increase the prediction performance. To validate this assumption, two typical cases using two public datasets are predicted and compared under different granularity levels using the standard stateful LSTM models. The results proved that predicting the appliances or submeters electricity consumption first and then aggregating the prediction can increase the prediction accuracy than making the direct prediction at the household level.

In the future, the spatial granularity needs to be analyzed further on other levels, for example, building levels, community levels, sub-transformer levels and so on. Besides, it is also meaningful to analyze the impact of temporal granularity on the prediction performance at the same level.

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