Short-Term Residential Load Forecasting Based on Resident Behaviour Learning

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***Abstract*—Residential load forecasting has been playing an increasingly important role in modern smart grids. Due to the variability of residents' activities, individual residential loads are usually too volatile to forecast accurately. A long short-term memory-based deep-learning forecasting framework with appliance consumption sequences is proposed to address such volatile problem. It is shown that the forecasting accuracy can be notably improved by including appliance measurements in the training data. The effectiveness of the proposed method is validated through extensive comparison studies on a real-world dataset.**

***Index Terms*—Deep learning, meter-level load forecasting, recurrent neural network, short-term load forecasting.**

I. Introduction

THE advanced metering infrastructure (AMI) has been rolling out to residential networks in many countries, which opens opportunities to improve grid energy efficiency through leveraging residential potential for demand response (DR). Many potential applications in future power system engineering such as demand side management (DSM), renewable energy source (RES) integration, and energy storage system (ESS) are heavily customer-oriented. In these cases, forecasting user-level energy consumption profiles is essential for DR program designs, home load scheduling with optimal RES objectives, and optimal ESS operations. Unlike electric load at the system level, domestic power consumptions are often with high volatility, which makes meter-level load forecasting for a single user extremely challengeable.

Meter-level load forecasting is a relatively new area. To the best of the authors' knowledge, a functional time series forecasting technique [1] and a Kalman filter estimator [2] are the only two studies that focus on single smart meter load forecasting. However, their works lack horizontal comparison with other benchmarks. In this letter, the main contributions are that we propose a deep learning based method with appliance behaviour learning for the meter-level load forecasting and demonstrate its advantageous performance through extensive comparisons with the other state-of-the-arts predictors.

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II. The Proposed Method

The electrical load on the system level is highly related to many contextual variables such temperature, humidity, the day of the week and special events. Unlike the aggregated load, the energy consumption of a residential house has a higher correlation to residents' behaviours. For example, a dweller may have a rather consistent daily routine such as taking a shower after breakfast, drying a load of laundry when the washing machine finishes, etc. If such patterns can be perceived, better forecasting performance can be expected.

A. Individual Load Forecasting Using LSTM

Long short-term memory (LSTM) is one of the recurrent neural network (RNN) structures. Although it has been successfully deployed in many real-world applications such as language translation, speech recognition and image captioning [3]–[5], it has not yet been applied in the electricity load forecasting community.

Sequence learning is a speciality of the LSTM model. Although a conventional feedforward neural network (FFNN) can also establish the correlation across time intervals by learning the "look-back" sequences, LSTM is more powerful because it maintains a memory cell in its structure to remember important state in the past and has a forget gate to learn to reset the memory cell for some unimportant features during the learning process.

B. Load Forecasting via Appliance Learning

As mentioned above, learning residents' life patterns is the key to achieving better meter-level forecasting. Although some lifestyle patterns may be hidden in the household-level energy profiles, learning such patterns from the whole-house data with 30-minute interval (the common sampling frequency of modern metering infrastructure) could be quite hard.

If appliance-level consumptions are directly measured, the lifestyle of the household is easier to identify, which may further assist in interpreting some volatility in the forecasting. Based on this realisation, instead of serving only aggregated energy data to the LSTM based predictor, in this study we propose to input all available major appliance energy sequences to train the predictor.

III. Test Cases and Results

In this study, AMPds is used for the proof of concept [6]. This dataset comprehensively records the minutely current readings of a Canadian household and its 19 appliances for a full year. We convert the current reading into Ampere hour for every 30 minutes to mimic commonly available smart meter data. Six representative manually

TABLE I
LSTM FORECASTING ARCHITECTURE BASED ON KERAS

```
Input (length in different scenarios {2, 3, 6, 12})
model.add(LSTM(hidden_neurons = 512, return_sequences = True))
model.add(LSTM(hidden_neurons = 512, return_sequences = False))
model.add(Dense(hidden_neurons = 512))
model.add(Activation('linear'))
model.add(Dense(1))
model.compile(loss = 'mae', optimizer = 'adam')
```

TABLE II
LOAD FORECASTING MAPE SUMMARY

Test Case/Scenario	*MAPE Avg.*	*Train. Time Avg. (sec)*	*Pred. Time Avg. (sec)*
LSTM-WA/2 time intervals	21.99%	829.13	0.33
LSTM-WA/3 time intervals	23.96%	959.15	0.44
LSTM-W/6 time intervals	26.23%	1272.85	0.82
LSTM-W/12 time intervals	26.85%	2094.28	1.53
FFNN-WA/3 time intervals	28.09%	25.36	0.01
FFNN-WA/2 time intervals	28.17%	24.58	0.01
FFNN-W/6 time intervals	30.68%	20.58	0.02
FFNN-W/12 time intervals	30.91%	26.22	0.01
KNN-WA/2 time intervals	26.86%	0.08	0.00
KNN-WA/3 time intervals	27.80%	0.10	0.00
KNN-W/6 time intervals	32.29%	0.02	0.00
KNN-W/12 time intervals	34.51%	0.05	0.00
FFNN-D-WA/2 days	27.66%	26.94	0.01
FFNN-D-WA/1 day	28.86%	36.74	0.01
FFNN-D-W/1 day	34.46%	37.92	0.02
FFNN-D-W/2 days	33.77%	37.50	0.01
Empirical Mean	50.20%	0.59	2.46

operated appliances, which are more relevant to residents' lifestyle, are picked for the appliance learning. They are clothes dryer, clothes washer, dishwasher, heat pump, television, and wall oven.

We experiment quite a few model settings with the Keras deep learning package [7] and settle on the architecture for meter-level short-term load forecasting given by Table I.

The proposed approach uses measurements of both the whole household consumptions and selected appliances from the past several time intervals until the current time as the inputs for resident behaviour learning. The output is the consumption forecast of the subsequent time interval.

To demonstrate the effectiveness of the proposed appliance learning approach, we compare the performance of the proposed method to several benchmarking results. The state-of-the-art candidates are the feedforward neural network (FFNN) and the k nearest neighbour (KNN). In addition to the few time steps "look-back" input scheme, a popular scheme in system-level load forecasting that uses measurements of the same time interval of the past few days is also compared, referred with the suffix "-D" hereinafter. We also use suffix "-WA" to label test cases that use extra appliance measurements in training data and "-W" for cases with whole house measurement only. The lowest benchmark is set by empirical mean, which simply outputs a forecasting value based on the statistical mean given the time of the day and the day type (weekday or weekend).

Both LSTM and FFNN based forecasting frameworks rely on random initialization of network weights. In order to evaluate their performances systematically, each forecasting scenario is performed ten times so that the forecasting results can reliably summarise as in Table II. The ranking of performances with one standard deviation error bars is given in Fig. 1. It is clearly seen that the proposed LSTM-WA forecasting framework outperforms all other benchmarking methods. Especially, the LSTM-WA with two look-back intervals achieves the best overall

Fig. 1. MAPE ranking with error bars of the leading scenarios.

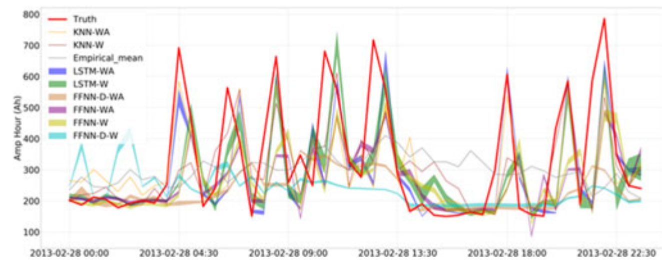

Fig. 2. Forecasting performance throughout a day for the leading scenarios.

MAPE scores and outperforms the second best LSTM-W predictor with a 4.24% MAPE margin. For FFNN and KNN, the versions with extra appliance data all outperform their counterparts with whole house consumptions only. This improvement confirms that resident behaviour learning through appliance consumptions can significantly improve the load forecasting performance.

In order to visualise how each method performs throughout a day, the forecasting upper bounds and lower bounds of each forecasting method at each time interval are plotted in Fig. 2. The figure also intuitively confirms that the LSTM-WA predicts the best for the load forecasting task during the day.

IV. CONCLUSION

Load forecasting for a single customer is hard due to the volatile nature of the individual. This letter shows the proposed LSTM recurrent neural network based forecasting framework performs better in establishing meaningful temporal relationships between consumptions across time intervals. Moreover, when consumption sequences of major appliances are available, they can further improve the meter-level forecasting accuracy under the proposed LSTM framework.

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