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A Whole System Assessment of Novel Deep Learning Approach on Short-Term Load Forecasting

Heng Shi, Minghao Xu, Qiuyang Ma, Chi Zhang, Ran Li, Furong Li

Department of Electronic and Electrical engineering, University of Bath, Bath, BA2 7AY, UK

Abstract

Deep learning has been proven of great potential in various time-series forecasting applications. To exploit the potential and extendibility of deep learning in electricity load forecasting, this paper for the first time presents a comprehensive deep learning assessment on performing load forecasting at different levels through the power systems. The assessment is demonstrated via two extreme cases: 1) regional aggregated demand with an example of New England electricity load data, and 2) disaggregated household demand with examples of 100 individual households from Ireland. The state-of-the-art deep recurrent neural network is implemented for this assessment. Compared with the shallow neural network, the proposed deep model has improved the forecasting accuracy in terms of MAPE by 23% at aggregated level and RMSE by 5% at disaggregated level.

Keywords: Load Forecasting; deep learning; multi-system levels; aggregation and disaggregation; smart metering; deep recurrent neural network

1. INTRODUCTION

The performance of the operation and planning programs, such as demand side response [1], active network management [2], economic dispatch [3], unit commitment [3, 4], and so on, highly relies on the accurate estimates of future load. With the decarbonisation of modern power sector, the largely increased intermittency and uncertainty are possessing huge challenges on traditional load forecasting methods [5]. Recent research has put significant effort on exploring novel load forecasting techniques to fit the modern power system with uncertainties.

With exceptional capability in exploiting complex features from the massive and high-diversity dataset, deep learning is regarded as one of the most promising techniques for forecasting in various applications. For instance, deep learning methods have been applied for stock prediction in the financial market [6], lung tumours movement forecasting [7] and traffic flow prediction in transportation sector [8, 9]. However, the investigation of deep learning application on electricity load forecasting is rather limited. [10] is the first to attempt deep learning method for electricity load forecasting at the system level. Their work is validated on a dataset with 20 zones in the USA. The

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proposed implementation of deep learning method is reaching the best performance compared to prior state-of-the-art [11] for system load forecasting. Deep Boltzmann Machine (DBM) is adopted in [12] to predict wind speed and achieves 10% performance enhancement to the best of existing techniques. The existing work has indicated a huge potential in applying deep learning to various forecasting activities in power systems. However, previous work only demonstrated the effectiveness of deep learning on two specific applications. It is a critical time now to assess the performance of deep learning models in forecasting at different levels of the power systems.

This paper for the first time presents a comprehensive assessment of deep learning method for load forecasting tasks through two extreme cases: i) regional aggregated demand with an example of New England electricity load data, and ii) disaggregated household demand with examples of 100 individual households from Ireland.

The unique contributions of this paper are:

i) exploited the potential deep learning by comparing the performance of between 'shallow' and 'deep' neural network;
ii) Investigated the extendibility of deep learning methods at differing aggregation levels across the whole system.

This paper is organized as follows: section 2 introduces recurrent neural network and deep recurrent neural networks; section 3 demonstrates the result and section 4 draws the conclusions.

2. INTRODUCTION

2.1. Recurrent Neural Network (RNN)

Recurrent neural network (RNN) refers to a specific neural network architecture, which is designed for processing sequential data $x^{(1)}, \dots, x^{(\tau)}$. Results of RNNs have shown success in time-series forecasting problems. A simple illustration of recurrent neural network is presented in Fig. 1.

RNNs attempt to map the input time series data $X = \langle x^{(1)}, x^{(2)}, \cdots, x^{(t)}, x^{(t+1)}, \cdots, x^{(T)} \rangle$ to the corresponding output $Y = \langle y^{(1)}, y^{(2)}, \cdots, y^{(t)}, y^{(t+1)}, \cdots, y^{(T)} \rangle$. The training process minimizes the differences between the output sequence Y and training targets of output. For a specific time step t, the learning mechanism of RNN can be described as follows [13]. In terms of the parameters, vectors b and c refers to the bias part. The weight matrices are noted as U, W, V, which represents the weight matrices that connect input-to-hidden, hidden-to-hidden and hidden-to-outputs.

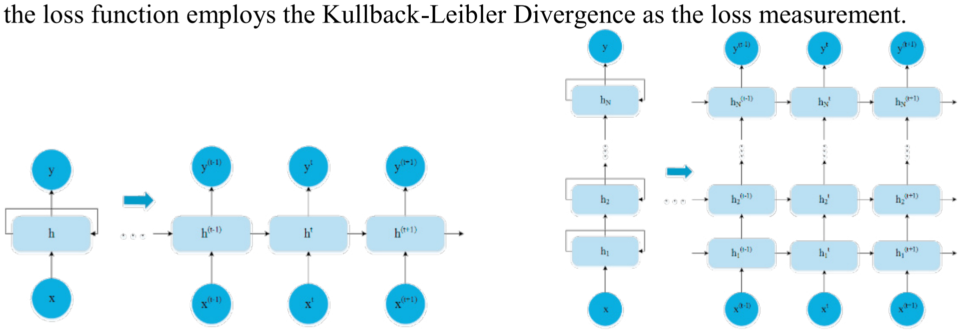
$$a^{(t)} = b + W \cdot h^{(t-1)} + U \cdot x^{(t)} \tag{1}$$

$$h^{(t)} = sigmoid(a^{(t)}) \tag{2}$$

$$y^{(t)} = c + V \cdot h^{(t)} \tag{3}$$

$$L = loss\_function(y^{(t)}, y^{(t)}_{target}) \tag{4}$$

Regarding the activation function, the typical implementation includes: sigmoid function, hyperbolic function (tanh) and rectified linear unit (ReLU). In this paper, sigmoid a function is employed as the activation unit. Furthermore, the loss function employs the Kullback-Leibler Divergence as the loss measurement.



a b

Fig. 1. The computational graph and unfolded topological graph of (a) RNN, (b) an N layers deep-RNN.