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Forecasting electricity load by a novel recurrent extreme learning machines approach

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ABSTRACT

Growth in electricity demand also gives a rise to the necessity of cheaper and safer electric supply and forecasting electricity load plays a key role in this goal. In this study recurrent extreme learning machine (RELM) was proposed as a novel approach to forecast electricity load more accurately. In RELM, extreme learning machine (ELM), which is a training method for single hidden layer feed forward neural network, was adapted to train a single hidden layer Jordan recurrent neural network. Electricity Load Diagrams 2011–2014 dataset was employed to evaluate and validate the proposed approach. Obtained results were compared with traditional ELM, linear regression, generalized regression neural network and some other popular machine learning methods. Achieved root mean square errors (RMSE) by RELM were nearly twice less than obtained results by other employed machine learning methods. The results showed that the recurrent type ANNs had extraordinary success in forecasting dynamic systems and also time-ordered datasets with comparison to feed forward ANNs. Also, used time in the training stage is similar to ELM and they are extremely fast than the others. This study showed that the proposed approach can be applied to forecast electricity load and RELM has high potential to be utilized in modeling dynamic systems effectively.

Introduction

Forecasting electricity load has traditionally been a major issue in planning, operating, expanding power system security and reducing operational costs for each of the power generation, transmission and delivery systems [2,11,22]. Forecasting electricity load was classified according to forecast duration into short, middle, and long-term forecasting and they are up to 24 h, few weeks and few months, respectively [22]. Long-term and middle-term prediction is generally utilized in planning new stations or transmission lines in the power transmission system [8]. On the other hand, short-term forecasting plays critical roles not only in managing power delivery system security [5] but also in electricity costs [13,22]. Therefore, forecasting short-term electricity has a major importance in smart grid [4,10]. The larger estimation errors yield higher operation costs. For instance, Hippert et al. [11] reported that 1% increase in the mean absolute percentage error of load forecasting caused a £10 million overpayment for operating costs in 1984. This overpayment comes from both under or overestimation of electricity load. In the case of underestimation, there is not only larger cost for demanded energy but also a probability of a shortage of generated power. That stems from the fact that, buying electricity in the last minutes is always more expensive and sometimes it is impossible. On the other hand, there is a waste of resources in the case of overestimation [8,25,26]. Due to these reasons, power delivery companies work hard for forecasting their electricity demand in a balance between under and overestimation. Unfortunately, forecasting the electricity load is a tricky issue, since large load variations are possible in a period of an hour or a day. These variations depend on many individual parameters such as weather conditions [5,22], temperature [20], day of week [20], hour of the day [11], seasonal factors [25,26], social activities [13] and socio-economic factors [8].

Owing to its significance, there is a large and growing literature in forecasting electricity load [7,23], which were generally concentrated on short-term prediction [18,20,5,11,3,8]. In these studies, not only statistical methods [7,23] but also machine learning methods were employed [27,18,20,5,11]. These models are built on establishing a relation between the electricity load and some of the relevant factors. Since these relations are generally nonlinear, machine learning methods achieved higher accuracies [22]. Alfares and Nazeeruddin [2] reviewed nine different forecasting approaches, which are statistical and machine learning methods. They reported that, the popularity of machine learning methods, such as artificial neural network (ANN) [20,5,11,3], fuzzy logic

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and support vector regression [13,25,26] were raised depending on their efficiency instead of statistical ones (for instance, state space and Kalman filter modeling), which showed limited forecasting accuracy. However, there are several successful attempts in forecasting load by ANN since 1991 [27,25,26,11,13], novel approaches are searched due to high economic profits that can be gained by a successful forecasting approach. Kermanshahi [16] and Pai and Hong [25,26] employed recurrent models, which were recurrent forms of ANN and support vector machine (SVM), and they reported that these methods outperformed their feed forward ones, where the fundamental difference between feed forward neural network (FFNN) and recurrent neural network (RNN) is feedback connections, which permits higher ability in modeling dynamical systems.

The motivation under this study is to develop an efficient way for forecasting electricity load. In recent years, there has been increasing interest in extreme learning machine (ELM), which is an extraordinary learning scheme for single hidden layer feed forward neural network (SHLFN) [15,14]. In ELM, the weights and biases of input layers are assigned randomly and the output weights are determined analytically. The results reported in the literature showed that ELM has high generalization capacity and extremely fast training stage not only in batch datasets [15,14] but also in time-ordered datasets [9]. Due to these facts, there are many versions of ELM in literature such as Self-Adaptive Evolutionary ELM (SaE-ELM) [31], Optimally Pruned ELM (OP-ELM) [6], multilayer-ELM [28]. This study is an attempt to transfer the gains of ELM for training RNN in order to achieve higher accuracy or lower estimation error and through this motivation recurrent ELM (RELM) was offered as a novel learning approach to train single hidden layer Jordan recurrent neural network (SHLRN).

To evaluate and validate the proposed approach, Electricity Load Diagrams 2011–2014 Dataset was utilized. Obtained results by the proposed approach showed higher accuracy than not only by traditional ELM but also by other employed popular machine learning methods, such as RNN, linear regression (LR), k-smooth regression (KSR), k nearest neighborhood regression (kNNR), Gaussian process regression (GPR) and generalized regression neural network (GRNN). The rest of the paper is structured as follows. Section 'Material and method' explains a brief overview of employed dataset, the proposed approach and the methodology of experiments. Section 'Results and discussion' presents results and outcomes of the proposed approach and finally, Section 'Conc lusion' concludes this study.

Material and method

Electricity Load Diagrams 2011–2014 Dataset

The Electricity Load Diagrams 2011–2014 Dataset was developed by Artur Trindade and shared in UCI Machine Learning Repository [19]. This dataset covers the electricity load of 370 substations in Portugal from the start of 2011 to the end of 2014 with a sampling period of 15 min. 10 stations were picked from the whole dataset for evaluating and validating the proposed approach. The datum belongs to select substations were analyzed through daily records and a sample from picked dataset was visualized in Fig. 1.

Extreme learning machine (ELM)

ELM is a training method for an SHLFN. As seen in Fig. 2, the output of SHLFN can be calculated by Huang et al. [15,14]:

$$y = \sum_{j=1}^{m} \beta_j g\left(\sum_{i=1}^{n} w_{i,j} x_i + b_j\right) \tag{1}$$

where x_i identifies input, y shows the output and m and n are the numbers of neurons in the hidden and input layers, respectively. $w_{i,j}$ is input weights, β_j is output weights, b_j is biases of the neurons in the hidden layer and $g(\cdot)$ is the activation function. Learning mechanism of ELM is built on obtaining zero error mean of the training dataset by $\sum_{i=1}^{N} \|y_j - t_j\| = 0$, where t is desired output and N indicates the number of instances in training dataset [14]. To achieve this purpose, input weights and biases are randomly assigned and the output weights are determined via the hidden layer output matrix (H), where the output of j^{th} hidden neuron [32] is:

$$H_{i,j} = g(w_j \cdot x_i + b_j) \tag{2}$$

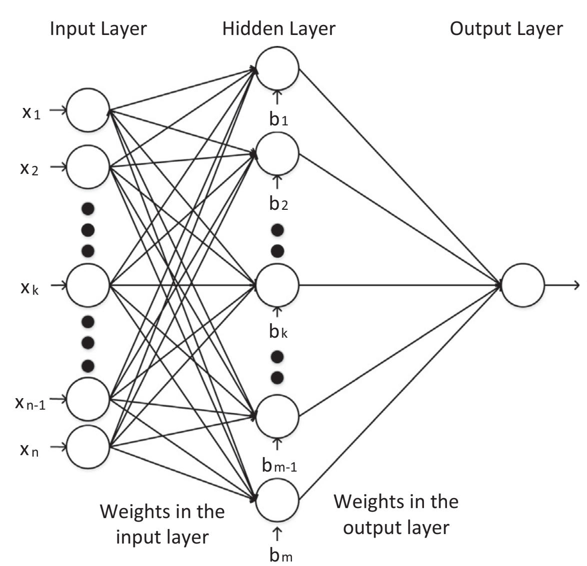

Fig. 2. The topology of single hidden layer feed forward neural network.

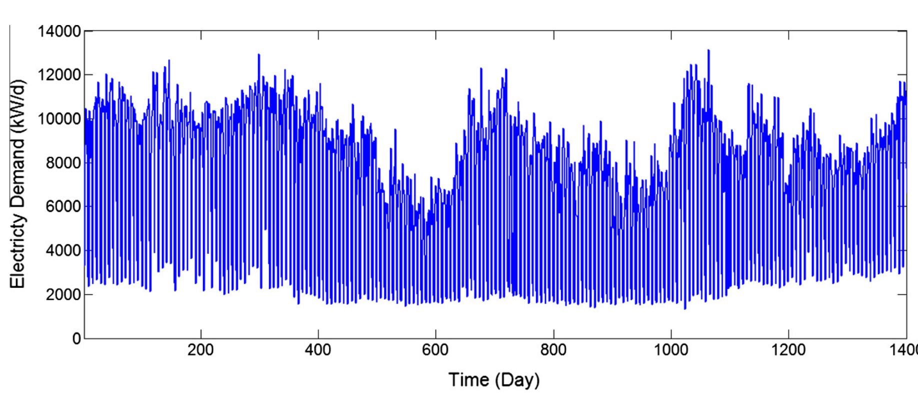

Fig. 1. A sample from employed dataset.