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Energy consumption prediction of office buildings based on echo state networks

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ABSTRACT

In this paper, energy consumption of an office building is predicted based on echo state networks (ESNs). Energy consumption of the office building is divided into consumptions from sockets, lights and air-conditioners, which are measured in each room of the office building by three ammeters installed inside, respectively. On the other hand, an office building generally consists of several types of rooms, i.e., office rooms, computer rooms, storage rooms, meeting rooms, etc., the energy consumption of which varies in accordance with different working routines in each type of rooms. In this paper, several novel reservoir topologies of ESNs are developed, the performance of ESNs with different reservoir topologies in predicting the energy consumption of rooms in the office building is compared, and the energy consumption of all the rooms in the office building is predicted with the developed topologies. Moreover, parameter sensitivity of ESNs with different reservoir topologies is analyzed. A case study shows that the developed simplified reservoir topologies are sufficient to achieve outstanding performance of ESNs in the prediction of building energy consumption.

1. Introduction

The increasing population, growing industrial production, fast economic development and rapid social progress in recent years have brought about huge demands for energy supplies and constantly rising energy consumption across the world, thereby resulting in a large number of environmental problems, including air pollution, water contamination, greenhouse effect, etc. [1,2]. In terms of energy consumption, buildings have become a focus of energy policy and decision making, since energy consumption from buildings accounts for a significant proportion throughout the world [3]. The proportion of building energy consumption in total energy consumption is approaching 40% in Europe [4], while it was 28% in China in 2011 and is expected to reach 35% by 2020 [5]. In order for decision makers to develop and implement policies to effectively reduce energy consumption from buildings, it is of great importance to establish accurate prediction of building energy consumption, with a view to alleviating environmental pollution to a certain extent and achieving sustainable development of human society. However, prediction of energy consumption is a great challenge due to factors including weather conditions, building structure, geographic location, settled population, seasonal changes, etc. [6,7].

During the past decades, a variety of techniques were applied to the prediction of building energy consumption, e.g., engineering methods [8], data mining techniques [9], neural networks (NNs) [10], clustering analysis [11], support vector machine (SVM) [12], fuzzy logic [13], etc. Among existing methods, NNs have been widely studied and applied to various fields, including system modeling [14], optimal control [15], fault diagnosis [16], and adaptive dynamic programming [17]. NNs are commonly divided into feedforward neural networks (FNNs) and recurrent neural networks (RNNs). Specifically, RNNs, which were widely used in nonlinear time-series prediction [18–21], have demonstrated their application to the prediction of building energy consumption [22]. However, traditional RNNs suffer from a high computational complexity in their training, which may lead to slow training, complex performance surfaces, and possible instability [23].

In recent years, echo state networks (ESNs), as a new type of RNNs proposed by Jaeger et al. [24,25], attracted great attention among researchers [26–31]. By using Markovian architectural bias of untrained RNNs to reflect historical inputs, ESNs utilize the dynamics created by a huge randomly created layer of recurrent units called reservoir, and only the connections between the reservoir and the output layer are modified in the learning process. In this way, the high computational complexity of traditional RNNs is significantly reduced, and the training efficiency is remarkably

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enhanced. The past decades have witnessed extensive studies on ESNs both in theory and practice.

Theoretical studies on ESNs focused on reservoir optimization mainly carried out from structure improvement and parameter selection. In [32], multiple network topologies were used for the generation of reservoir, including small-world network, scale-free network, etc. Deng and Zhang [33] proposed a reservoir topology with small-world and scale-free properties. Song and Feng [34] investigated a cortex-like network generation method to construct the reservoir and therefore discovered an improved design strategy for the reservoir. Rodan and Tino [35] developed three simple reservoir topologies called delay line reservoir (DLR), DLR with feedback connections (DLRB) and simple cycle reservoir (SCR), respectively, which achieved good performance in time-series processing. In [36], a stochastic gradient descent method was developed to optimize global learning parameters including input and output feedback scalings, leaking rate and spectral radius of ESNs. Steil [37] optimized the reservoir by adopting a biologically motivated learning rule based on neural intrinsic plasticity (IP). In [38,39], the learning rule of IP was applied to tuning the probability density of all the neurons' outputs towards an exponential distribution and Gaussian distribution, respectively, which realized maximization of information. On the other hand, ESNs have achieved wide practical applications in various fields, including chaotic time-series prediction [40–42], dynamic pattern extraction [43], speech recognition [44], noise modeling [25] and complex signal filtering [45]. Specifically, ESNs have demonstrated outstanding performance in time-series prediction with real-life measurements [46–49].

Inspired by [35], several simplified reservoir topologies of ESNs are developed in this paper, and then ESNs with these different reservoir topologies are applied to the prediction of building energy consumption, which fully utilizes the remarkable performance of ESNs in chaotic time-series prediction. The main contributions of this paper are summarized as follows:

(1) A total of six simplified reservoir topologies of ESNs including two novel ones are developed and described in detail.

(2) The energy consumption in an office building is predicted by ESNs with different reservoir topologies, and their prediction performance is compared.

(3) The parameters of different topologies are summarized, and a sensitivity analysis is conducted to show the influence of these parameters on the prediction performance of the ESNs.

The rest of the paper is organized as follows. Basic knowledge on ESNs is given in Section 2. Several different reservoir topologies of ESNs are developed in Section 3, and related parameters of the topologies are summarized. A detailed case study with a parameter sensitivity analysis is given in Section 4 to show the performance of the developed topologies in the prediction of building energy consumption. Finally, the conclusion is drawn and future work is presented in Section 5.

2. Preliminaries of ESNs

As shown in Fig. 1, an ESN is a discrete-time RNN composed of an input layer, a reservoir and an output layer. The reservoir contains a large number of interconnected dynamic units, which are called reservoir units in this paper. The output layer is a memoryless linear readout trained to generate the output.

It is assumed that an ESN has K input units, N reservoir units and L output units. Activations of the input, reservoir and output units at time step t are denoted by s_t, x_t and o_t, respectively, where $s_t \in R^K$, $x_t \in R^N$ and $o_t \in R^L$. Connections between input units and reservoir units are collected in an $N \times K$ weight matrix W^{in}, connections between reservoir units are collected in an $N \times N$ weight matrix W, while connections between reservoir units and output units are collected in an $N \times L$ weight matrix W^{out}. Therefore, the activation of reservoir units is updated as

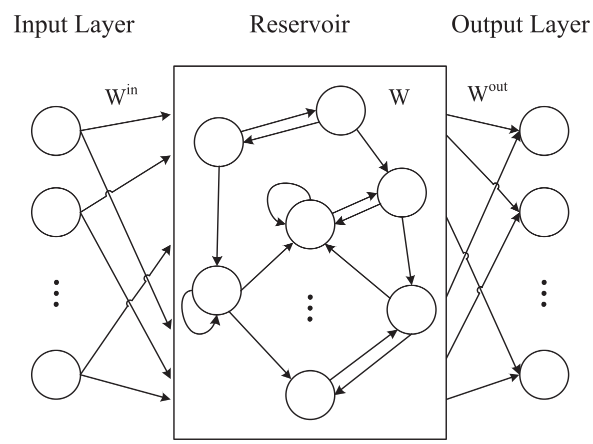

Fig. 1. Basic structure of an ESN.

$$x_t = f(W^{\text{in}} \cdot s_t + W \cdot x_{t-1}), \tag{1}$$

where $f = \tanh$ is the activation function of the reservoir. The linear output is calculated as

$$o_t = (W^{\text{out}})^T \cdot x_t. \tag{2}$$

Elements of W^{in} and W are randomly initialized from a continuous probability distribution before training. In order to guarantee the echo state property (ESP) of reservoir units, the reservoir weight matrix W is usually scaled by $\eta W/\rho \to W$, where $0 < \eta < 1$ is a scaling parameter and ρ is the spectral radius of W.

Remark 1. As given in [50,51], setting the spectral radius of W less than 1 is only a necessary condition to guarantee the ESP of reservoir units, however, the necessary condition is often sufficient in most practical cases owing to the contractive dynamics of the reservoir with the nonlinear activation function $f = \tanh$.

During the training of the ESN, W^{in} and W are fixed, and only W^{out} is tuned. Therefore, given M training samples and based on (1) and (2), we can obtain the following equation

$$\mathcal{H} W^{\text{out}} = O, \tag{3}$$

where the matrix $\mathcal{H}$ called reservoir output matrix is constructed as

$$\mathcal{H}\left(w_1^{\text{in}}, \ldots, w_N^{\text{in}}, w_1, \ldots, w_N, s_1, \ldots, s_M, x_0, \ldots, x_{M-1}\right) = \begin{bmatrix} f\left(w_1^{\text{in}} \cdot s_1 + w_1 \cdot x_0\right) & \cdots & f\left(w_N^{\text{in}} \cdot s_1 + w_N \cdot x_0\right) \\ \vdots & \ddots & \vdots \\ f\left(w_1^{\text{in}} \cdot s_M + w_1 \cdot x_0\right) & \cdots & f\left(w_N^{\text{in}} \cdot s_M + w_N \cdot x_{M-1}\right) \end{bmatrix}_{M \times N}, \tag{4}$$

and

$$W^{\text{out}} = \begin{bmatrix} \left(w_1^{\text{out}}\right)^T \\ \vdots \\ \left(w_N^{\text{out}}\right)^T \end{bmatrix}_{N \times L}, \quad \text{and} \quad O = \begin{bmatrix} o_1^T \\ \vdots \\ o_M^T \end{bmatrix}_{M \times L}. \tag{5}$$

We can calculate the minimum norm least-square solution of the linear system (3) as the output weight matrix of the ESN,

$$\hat{W}^{\text{out}} = \mathcal{H}^{\dagger} O, \tag{6}$$

where $\mathcal{H}^{\dagger}$ is the Moore–Penrose generalized inverse of matrix $\mathcal{H}$ [52,53].

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