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A hybrid teaching-learning artificial neural network for building electrical energy consumption prediction

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ABSTRACT

Numerous data-driven models have been successfully adopted for electrical energy consumption forecasting at building and larger scales. When the data set for forecasting is multi-sourced, heterogeneous or inadequate, single data-driven model may lead to convergence problem or poor model accuracy. The combination of advanced evolutionary algorithms (EAs) and data-driven models is proved effective in terms of prediction accuracy and robustness improvements. However, some of them are very time consuming to converge. In this paper, a novel EA, i.e. teaching learning based optimization (TLBO), is proposed for short-term building energy usage prediction. To enhance its convergence speed and optimization accuracy, the basic TLBO algorithm is further modified in three aspects. The improved algorithm is combined with artificial neural networks (ANNs) and applied to hourly electrical energy prediction of two educational buildings located in USA and China respectively. Performance comparisons show that the proposed model has superior performances than previously reported GA-ANN and PSO-ANN methods in terms of convergence speed and predictive accuracy, and is suitable for online energy prediction in the future.

1. Introduction

Rapid economic growth, accompanied by structural changes, strongly affects the global trend of energy consumption [1]. For building sector, energy use prediction contributes to effective building energy management, energy systems commissioning through detecting system faults, building energy operation and control, etc. Many computer softwares have been developed for energy efficiency design of new buildings, e.g. EnergyPlus, eQUEST, BLAST, DeST, etc. But for existing buildings, it is difficult to estimate future energy usage because a number of multi-sourced factors influence the building energy behavior, e.g. weather conditions, building materials' thermal properties, occupancy schedule, not to speak of the complex interactions of HVAC and lighting systems.

In the past two decades, numerous data-driven methods were introduced to the area of building energy prediction. These techniques modeled building energy usage patterns based on previously recorded time series data, such as past energy usage data, weather conditions, occupancy schedule, etc. Recent review studies had offered detailed classification of the existing predictive models and their characteristics. Zhao and Magouls [2] provided a review on major prediction methods of building energy consumption and classified them into five categories, i.e. engineering approaches, statistical models, artificial neural networks (ANNs), support vector machines (SVMs), and grey models (GMs). Wang and Srinivasan [3] reviewed artificial intelligence (AI) based building energy forecasting. Two categories of AI based prediction methods, i.e. the single prediction methods and the ensemble prediction methods, were discussed and compared. Deb et al. [4] provided a review on time series forecasting techniques for building energy consumption. Nine major time series techniques (ARIMA, ANN, SVM, Hybrid, etc.) with respect to building energy usage were compared and analyzed. Daut et al. [5] reviewed conventional and AI methods for building electrical energy consumption prediction. For the purpose of accuracy improvement, the swarm intelligence methods were surveyed to be hybridized with single data-driven models.

Above reviews provided very beneficial information on numerous forecasting models at different space and time scales. Hybrid AI models for building energy forecasting are popularly used, and recent case studies from 2010 to 2017 are briefly reviewed in the next section. It is noted that most research works focused on prediction accuracy improvement, but the modeling time issue, which is important for online application, is seldom addressed. This study emphasizes on the development of a new evolutionary algorithm

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Nomenclature

ANN	Artificial neural network
ARIMA	Autoregressive Integrated Moving Average
ANFIS	Adaptive neuro-fuzzy inference system
TLBO	Teaching learning based optimization
iTLBO	Improved teaching learning based optimization
WBE	Whole building electric power consumption (kW)
CV	Coefficient of variation of the root mean square deviation
MAPE	Mean absolute percentage error
r	Random number between (0,1) obeying uniform distribution
TF	Teaching factor, random number obeying uniform distribution
AF	Accuracy factor
FES	Function evaluations
NP	Number of population
D	Problem dimension
X	Teacher or learner in TLBO
$h(t)$	The hour of the day
$T(t)$	Outdoor dry bulb temperature (°C)
$S(t)$	Solar radiation (W/m^2)
s	Occupancy flag
sh	Sine of the hour of the day
ch	Cosine of the hour of the day
R	Covariance matrix
S_{ij}	Covariance of original variables
λ	Eigenvalue vector of R
EA	Evolutionary algorithm
PCA	Principal component analysis

(EA) based predictive models for short-term building electrical energy prediction. The novel EA, i.e. teaching learning based optimization (TLBO) is proposed to improve the modeling performances of regular artificial neural networks (ANNs). To enhance its capabilities of convergence speed and precision, the basic TLBO is further modified using three different measures. By integrating the characteristics of improved TLBO (iTLBO) and ANN, the iTLBO-ANN hybrid predictive models are applied to two educational buildings for hourly electrical energy consumption forecasting. Performance comparisons with previous AI models are investigated. Results validate the effectiveness and efficiency of the proposed method.

The study is organized as the following: Section 2 provides a short review of current research trends of energy use prediction. Section 3 presents the theories, structure and characteristics of the iTLBO-ANN model. Section 4 gives the data description of two applications for model validation. Section 5 provides the predictive applications' results and discusses the capabilities of the hybrid model compared with other EAs based methods. Finally, conclusions are provided in Section 6.

2. Short review of building energy usage prediction from 2010 to 2017

During the past decade, there were numerous data-driven models for building energy usage prediction, which included regression model, artificial neural networks, support vector regression, fuzzy model, grey model, etc. For example, Yun et al. [6] used an indexed fourth order auto regressive model for one hour ahead building heat load forecasting. Korolija et al. [7] developed bivariate and multivariate regression models for predicting long term building's heating, cooling and auxiliary energy requirements of various HVAC systems. Caicedo et al. [8] forecasted lighting system's energy performance using sensor data based support vector regression (SVR) model. Jain et al. [9] presented a forecasting model based on SVR, and applied it to predict energy consumption of multi-family residential buildings in New York City. Ekici and Aksoy [10] used an adaptive neuro-fuzzy inference system (ANFIS) to forecast building energy load in a cold region. Among the existing prediction approaches, ANNs are very popular and widely applied in recent years. Since 2010, Deb et al. [11] applied a feed-forward ANN with 'Bayesian regularization' training algorithm to forecast diurnal cooling energy load of institutional buildings in Singapore. Mena et al. [12] developed a three-layer ANN structure for short-term electricity load prediction of a bioclimatic building, located in the southeast of Spain. Kouhi and Keynia [13], in 2013, applied a cascaded ANN for short-term energy prediction of the power system in PJM and New York. Three cascaded ANNs with Levenberg–Marquardt (LM) learning algorithm were constructed for 24 h ahead prediction. Chae et al. [14], in 2016, proposed a short-term building electrical consumption forecasting method based on ANN model combined with Bayesian regularization algorithm. Due to the highly noisy input data for sub-hour prediction, random forests algorithm was applied to estimate the correlation of input variables. In the design phase, EnergyPlus and other simulation softwares can also be combined with AI for building energy estimation [15].

In general, for the applications of energy load forecasting, ANN methods are very popular and capable of providing reliable results with good accuracy. However, they also have some disadvantages needed to be acknowledged:

- The model training for convergence is time-consuming.
- It is easy to fall into the local optimal due to the gradient-based learning algorithm.
- The selection of network structure needs professional knowledge.
- The model precision is hardly dependent on samples which make the proper data selection very critical.

Recently, a plenty of AI based hybrid models have been widely adopted in the area of building energy forecasting. Chaturvedi et al. [16], in 2015, integrated adaptive genetic algorithm (GA) with ANN to overcome the limitations of back-propagation training approach. The authors applied the hybrid method for the short-term electrical load forecasting problem. Moazzami et al. [17] presented a GA hybridized ANN model for national-wide daily peak load forecasting. In their method, GA was used to select the model inputs, the step size, momentum values, and neuron number. Similarly, Defilippo et al. [18] applied GA to help select the proper architecture and training parameters of an ANN for electrical load forecasting. The comparative simulation revealed that GA based ANN produced much better robustness and accuracy than other benchmarks. Li et al. [19], in 2015, improved particle swarm optimization (PSO) algorithm and proposed an iPSO-ANN model for building's electrical consumption prediction. The iPSO algorithm was used to optimize ANN's weights and threshold values in the global scope. Investigation results illustrated its superior performance compared with basic ANN and GA-ANN methods in term of forecasting accuracy. Wang et al. [20] improved an ARIMA model by employing residual modification models for electricity demand prediction. A PSO-optimized Fourier approach was introduced to improve the residual errors. Chen et al. [21] combined PSO and SVM model for electrical load forecasting in South Australia. In their method, PSO was applied to adjust SVM's important parameters. Son and Kim [22] applied PSO algorithm to search the optimal variable subset used for SVM training. The regularization parameter and kernel parameter of SVM were adjusted by another algorithm, so called grid-search approach. Similarly, for variable subset selection of SVM, ant colony optimization (ACO) was applied by Niu et al. [23] in 2010. With the ACO combination method, SVM training data was successfully reduced, and the slow processing speed