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Machine learning-based thermal response time ahead energy demand prediction for building heating systems☆

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HIGHLIGHTS

- Machine learning-based models are proposed to predict energy demand for building heating.
- Seven meteorological parameters and indoor temperature are used as feature variables.
- An estimation approach of building thermal response time is presented.
- The prediction performances of four machine learning models are studied.
- The ELM model using FS4 performs the best with the prediction RMSE of 3.824.

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ABSTRACT

Energy demand prediction of building heating is conducive to optimal control, fault detection and diagnosis and building intelligentization. In this study, energy demand prediction models are developed through machine learning methods, including extreme learning machine, multiple linear regression, support vector regression and backpropagation neural network. Seven different meteorological parameters, operating parameters, time and indoor temperature parameters are used as feature variables of the model. Correlation analysis method is utilized to optimize the feature sets. Moreover, this paper proposes a strategy for obtaining the thermal response time of building, which is used as the time ahead of prediction models. The prediction performances of extreme learning machine models with various hidden layer nodes are analyzed and contrasted. Actual data of building heating using a ground source heat pump system are collected and used to test the performances of the models. Results show that the thermal response time of the building is approximately 40 min. Four feature sets are obtained, and the performances of the models with feature set 4 are better. For different machine learning methods, the performances of extreme learning machine models are better than others. In addition, the optimal number of hidden layer nodes is 11 for the extreme learning machine model with feature set 4.

1. Introduction

Building energy consumption has constantly increased in recent years, this increase comprises approximately 40% of the total energy consumption in developed countries [1]. More than 50% of building energy consumption is used for heating, cooling and domestic water heating in China. Therefore, reducing the energy consumption of building heating system is crucial to building energy saving. The energy demand forecast for building heating plays a significant role in heating, ventilation and air conditioning (HVAC) system optimization control, fault diagnosis and building intelligentization [2–4]. Halvgaard et al. [5] developed a heat load forecasting model as part of the Model Predictive Control for providing demand response. Cooling load prediction models were established based on general regression neural networks to optimize an HVAC thermal energy storage in the public and office buildings [6]. Wang et al. [7] used weekly and daily energy consumption prediction models in implementing comprehensive building energy performance diagnosis. Pedersen et al. [8] developed a load prediction model for heat and electricity demand in the building, and it could be used to plan for mixed energy distribution systems. Ground

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Nomenclature

a_i	the coefficients of the polynomial
b_i	threshold of the hidden layer
E	predicted error of the neural network
E_t	current energy demand, kWh
$E_{t+40\text{min}}$	40 min ahead energy demand, kWh
H	hidden layer output matrix
$H_{outdoor}$	outdoor environment humidity, %
L	light intensity, Lux
N	number of input variables
Q_k	predicted value of output layer of neural network
r	the correlation coefficient between two variables
R	radiation intensity, W/m^2
t_k	expected output of neural network
T	expected output
$T_{outdoor}$	outdoor temperature, °C
T_{return}	returning GSHP system water temperature, °C
T_{supply}	supplied GSHP system water temperature, °C
$T_{outdoor,int}$	integrated outdoor temperature, °C
T_{indoor}	indoor temperature, °C
V_{speed}	outdoor wind speed, m/s
$V_{direction}$	outdoor wind direction
y	predicted value
Y_i	predicted value
$\hat{Y}_i$	actual value

Greeks

ω_i	connection weight between the input layer and hidden layer
γ	width of Gaussian kernel function
δ	regression coefficients during LASSO feature selection
β	weight of output layer
$\hat{\beta}$	optimal weight of output layer

source heat pump (GSHP) system, as a highly efficient and environment-friendly building heating system, has been extensively used in various types of buildings [9,10]. The present study focuses on a building heated by the GSHP system.

At present, studies on energy demand forecasting are mainly divided into two categories, namely, the white box model and the black box model [11]. The white box model is based on the physical method and requires numerous detailed attributes. The black box models mainly use machine learning methods [12], such as neural networks, multiple linear regression (MLR). Lisa [13] developed several models for forecasting the electrical load for supermarket refrigeration during opening and closing hours. Linear regression, random forest and support vector regression (SVR) algorithms are used to establish electricity prediction models at the city scale [14]. Jain et al. [15] established the building energy prediction model using the SVR for multi-family residential buildings. Wang et al. [16] used an ensemble bagging tree method to develop an institutional building electricity demand prediction model and applied data permutation-based feature selection to reduce the computation time of the model. Muralitharan [17] developed an energy demand prediction model by using an neural network that was optimized by genetic algorithm and particle swarm optimization approaches. Fan et al. [18] established an ensemble model though data mining methods to predict next-day energy consumption and peak power demand. Al-Shammari et al. [19] developed short-term multistep-ahead predictive models based on combined support vector machine and firefly algorithm for the heat load of the district heating system. The neural network approach was used to establish a daily steam load model [20]. Deep learning-based methods were developed for building cooling load prediction [21]. Sun et al. [22] developed an optimized SVR model based on outlier detection methods for predicting electricity consumption of a public building GSHP system. However, there are few studies on the energy demand prediction of building heating using extreme learning machine (ELM) method. The ELM method has been widely used in image and pattern classification [23,24], clustering [25] and prediction fields. Zhang et al. [26] developed an electricity price forecasting model using wavelet and ELM methods. The short-term wind speed prediction model was established based on ELM with error correction [27]. Therefore, this study uses the ELM method to establish the models to study its potential in the field of energy demand prediction. Moreover, the three other machine learning methods, which are MLR, BP neural network (BPNN) and SVR methods, have been applied mathematically in energy demand forecasting [12,28–30]. To compare with the ELM model, these three machine learning methods are also selected to develop energy demand prediction models. Their predictive performance will be compared and analyzed.

The selection of feature variables also plays a vital role in the performance of energy demand prediction models. However, most of the existing models only use the meteorological attributes [29,31–33]. Several of these models only utilize the outdoor temperature in meteorological parameters [34–36]. These models don't consider the effects of other meteorological parameters and the indoor temperature on heating energy demand forecasting. In the present study, the energy demand prediction models are established by seven meteorological parameters, operating parameters, time and indoor temperature. In addition, the correlation analysis method and Least Absolute Shrinkage and Selection Operator (LASSO) feature selection approach are used to optimize the feature variable set.

After determining the input parameters of the model, the output prediction parameters also need to be defined. It is essential to determine the time intervals ahead of energy demand of the models. Fan et al. [21] developed a short-term building cooling load prediction model to predict a 24-h ahead building cooling load profile. Ensemble

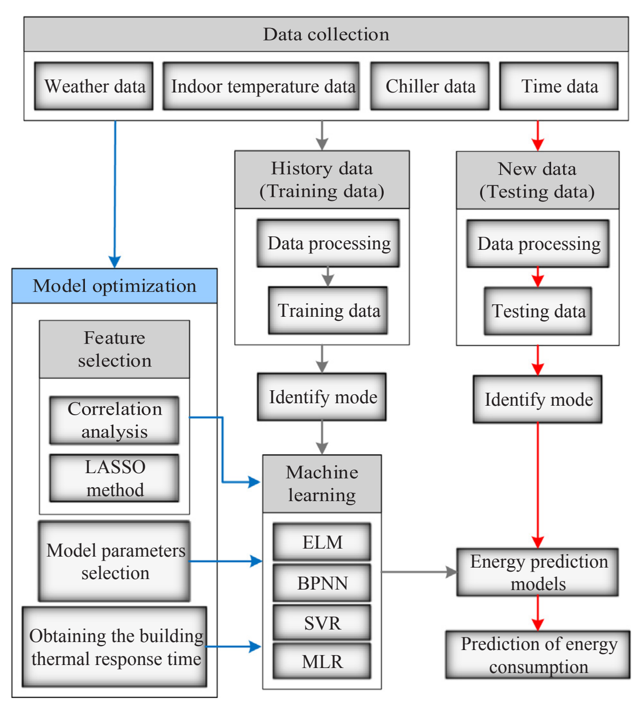

Fig. 1. Framework of the developed energy prediction models.