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Medium-term heat load prediction for an existing residential building based on a wireless on-off control system

Jihao Gu [a], Jin Wang [a, *], Chengying Qi [a], Chunhua Min [a], Bengt Sundén [b]

[a] School of Energy and Environmental Engineering, Hebei University of Technology, Tianjin 300401, China
[b] Department of Energy Sciences, Division of Heat Transfer, Lund University, P.O. Box 118, SE-22100 Lund, Sweden

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ABSTRACT

For district heating systems, prediction of the heat load is a very important topic for energy storage and optimized operation. For large and complex heating systems, most prediction models in previous publications only considered the influence of outdoor temperature, whereas the indoor temperature and thermal inertia of buildings were not included. For an energy-efficient residential building in Shijiazhuang (China), the heat load prediction is investigated using various prediction models, including a wavelet neural network (WNN), extreme learning machine (ELM), support vector machine (SVM) and back propagation neural network optimized by a genetic algorithm (GA-BP). In these models, the indoor temperature and historical loads are considered as influencing factors. It is found that the prediction accuracies of the ELM and GA-BP are slightly higher than that of WNN, so the ELM and GA-BP models provide feasible methods for the heat load prediction. The SVM shows smaller relative errors in the model prediction compared with three neural network algorithms.

1. Introduction

In recent years, the building energy consumption has a rapid growth. According to the statistics as shown in Ref. [1], this energy consumption accounts for around 20–40% of the total number in advanced countries. He et al. [2] indicated that the share of the heating energy consumption in northern China is above 20%. Prediction of the heat load is the foundation for operating management of many buildings. The heat load prediction includes short-term (from seconds to hours), medium-term (from days to months) and long-term forecasting (from months to quarters or even years), and is affected by the buildings physical properties, outdoor temperature, indoor temperature and household behavior [3]. Recently, most of the heat load forecasting models are of the short-term forecast type [4]. Massana et al. [5] used an autoregressive model (AR) to predict the short-term heat load for non-residential buildings. In this model, influence of the historical load was only investigated without considering climate parameters. Protić et al. [6] showed forecasting models which used the support vector regression with a polynomial (SVR-POLY) and the support vector regression with a radial basis function (SVR-RBF) to predict the heat load for a heating substation in Serbia. The two models included outdoor temperature, primary supply temperature, primary return temperature and instantaneous flow on the primary side, but without considering the indoor temperature. Powell et al. [7] predicted the heat load for the main campus at the University of Texas (1.6 million m^2) for the next 24 h using a nonlinear autoregressive external input model (NARX) of time series. They showed that the mean absolute percentage error (MAPE) of this prediction model was 9.8%. Al-Shammari et al. [8] forecasted the heat load for a district heating system in Novi Sad for the next 10 h using the support vector machine with the firefly algorithm (SVM-FFA). The results indicated that the method was only suitable for a short-term prediction. Fang et al. [9] predicted the heat load for the city Espoo in Finland for 168 h using a mixed model, which was based on a combination of a multiple linear regression analysis model (MLRM) and a seasonal autoregressive differential moving average model (SARIMA). However, the effect of the indoor temperature was not considered in this mixed model. Idowu et al. [10] predicted a short-term (24 h) heat load for five residential buildings and five commercial buildings by using support vector machine (SVM), feed-forward neural network (FFN), multiple linear regression (MLR) and regression tree algorithm (RT). The results proved

* Corresponding author.
E-mail addresses: jihaogu@hebut.edu.cn (J. Gu), wjwcn00@163.com (J. Wang), qicy@hebut.edu.cn (C. Qi), chmin@hebut.edu.cn (C. Min), Bengt.Sunden@energy.lth.se (B. Sundén).

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Nomenclature

a	scaling factor
b	translation factor of wavelet basis function
F	area (m^2)
G	instantaneous water flow of the entrance (m^3/h)
h	output values of the hidden layer
l	number of hidden layer nodes
m	number of rooms
Q	heat consumption (kWh)
T	temperature (K)
X	input parameter
Y	output parameter
$\boldsymbol{z}$	number of output layer nodes

Greek symbols

ω	weight of the wavelet neural network
τ	accumulative proportion

Superscript

H	the Hth order
M	the Mth order
N	the Nth order
Z	the Zth order

Subscripts

d	daily-averaged
h	hourly-averaged
i	instantaneous
j	the jth order
in	indoor
out	outdoor
p	prediction
r	return
s	supply
t	transient

that the SVM was the optimal method for heat load prediction. Protić et al. [11] forecasted the heat load for heat supply units in the city Novi Sad by comparing the accuracies of support vector machine with discrete wavelet transform algorithm (SVM-WAVELET), extreme learning machine (ELM), artificial neural network (ANN) and genetic programming algorithm (GP). They found that the SVM-WAVELET had the highest computational precision. Sajjadi et al. [12] compared the extreme learning machine (ELM) with genetic programming (GP) and artificial neural network (ANN) models to predict the heat load for a district heating system. The results showed that the accuracy and generalization ability of ELM was superior to GP and ANN. Without consideration of the influence of the outdoor temperature, Shamshirband et al. [13] found that prediction errors gradually increased with the time step when the adaptive neuro-fuzzy inferences system (ANFIS) was used. Sholahudin S [14] presented a dynamic neural network method to forecast the heat load for a typical 9-story apartment building in Seoul, and the research results showed that the outdoor temperature and wind speed were the greatest influencing factors on the instantaneous heat load. Chou et al. [15] used ANN, SVM, classification and regression tree algorithm (CART), chi-square automatic verification algorithm (CHAID) and general linear regression (GLR) to predict the energy consumption of a building. The SVM method was proved to be the best method and the MAPE of this model was 1.13%. Zhang et al. [16] predicted the heat load for a heat source in the Hebei province, China. The study indicated that cross validation and automatic parameter optimization based on the SVR method can improve the prediction accuracy. Cheng et al. [17] predicted the cooling load of a building for the next 24 h using the deep learning algorithm. However, the used two-week data set was not large enough to ensure reliable training of this prediction model. Dahl et al. [18] predicted the heat load for a district heating system in Aarhus using various ensemble weather factors, including outdoor temperature, wind speed and solar radiation, but without indoor temperature. For a non-energy-efficient building, the heat load changes significantly with instantaneous outdoor temperature due to the poor thermal insulation. However, for an energy-efficient building, the heat load mainly fluctuates due to the outdoor daily-averaged temperature [19].

Above all, many studies focused on discussions of short-term (below 48 h) prediction models, but there was only few data available to predict a medium-term (a week) heat load. Most of the prediction models only considered effects of climate factors, whereas the indoor temperature and the thermal inertia of the buildings were ignored. In addition, the climate condition, especially the outdoor temperature, is one of the most significant factors that affect the heat load [20,21].

Without taking into account the indoor temperatures as in most existing models, the predicted data will give an inaccurate prediction. Therefore, the aim of this research is to investigate effects of the indoor temperature of the heating system, and thereby provide a more accurate prediction method. In addition, combined with the weather forecast and the setting indoor temperature, comparisons of WNN, ELM, GA-BP and SVM are conducted to predict the heat demand of buildings.

2. Measurement system

2.1. A wireless on-off control system

A wireless on-off control system was developed to adjust the indoor temperature as shown in Fig. 1. A calorimeter was installed at the entrance of a chosen building to measure the total heat consumption of the building. The wireless indoor temperature controller and on-off valves were installed for each household. The indoor temperature controller can adjust the room temperature and collect temperature information of each household. The description of this operating process is as follows: firstly, after the indoor temperature is set by the user through the temperature controller, a wireless signal is sent to the wireless on-off valve. Then the real indoor temperature is detected by the valve. All the controllers are comparing the set and the real values. If the real value is different from the set value, the valve will open or close.

The calculation formula of the heat metering system is described as [22]:

$$Q_j = \frac{\tau_j F_j}{\sum_{j=1}^{m} \tau_j F_j} Q \tag{1}$$

where Q_j is the heat allocated for the household j; τ_j is the accumulative proportion of open time of the valve for household j; F_j is the heating area of household j; Q is the heat consumption of the building, and m is the number of rooms. According to Equation (1), the heat consumption of the building is shared with all the households by considering effects of the heating areas and