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The re-optimization strategy of multi-layer hybrid building's cooling and heating load soft sensing technology research based on temperature interval and hierarchical modeling techniques

Kai Liu[a,b], Ting-Zhang Liu[a,b,*], Pan Jian[a,b], Yue Lin[a,b]

[a] Department of Automation, College of Mechatronics Engineering and Automation, Shanghai University, China
[b] Shanghai Key Laboratory of Power Station Automation Technology, Shanghai, China

A R T I C L E I N F O

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A B S T R A C T

To avoid expanding existing fossil power plants, building the energy performance management system is an effect method to cope with a high growth demand of electricity in China's urbanization process. The accuracy thermal load prediction is the first step to build an energy performance management system which has important significance for energy saving, decreasing air pollution and high-efficiency operation of HVAC system.

This paper discusses the use of hybrid intelligent approaches and re-optimization strategy, a multi-layer hybrid model (APNN) has been proposed by hybridizing an auto-regressive model with exogenous inputs (ARX) and a particle swarm optimization neural network (PSO-NN) to make a good use of the comprehensive information of the meteorological data and historical data. For the purposes of improving prediction precision generalization ability of the multi-layer hybrid model, temperature interval and hierarchical modeling techniques were used. According to the re-optimization strategy, there are two improvements of the previous proposed APNN model, which are based on temperature interval and hierarchical modeling by solar radiation intensity. Compared with the basic prediction models, validation results show that accuracy of the optimized models are greatly improved. What's more, the optimization of multi-layer hybrid building's cooling and heating load soft sensing technology enhance learning and generalization capability of the basic APNN model.

1. Introduction

With the rapid worldwide urbanization progress, building energy consumption has received much more attention from both research institutions and governments (IPCC, Climate Change, 2007; Levine et al., 2007; Levermore, 2008). There has been much research on energy consumption, the research of Kwok and Rajkovich (2010) showed that the amount and cost of energy from building sector accounted for 38.92% of the total primary energy requirements (PER) of the United States. China, with Hong Kong included, was the biggest energy user in 2015, consuming 4.30 billion tons of coal equivalents, building sector energy consumption is estimated to increase to approximately 35.12% in 2020 (Lang, 2002; Yao, Li, & Steemers, 2005). Although carbon emissions per capital in China are lower than those in other developed countries, its total emissions are the second only to the US. From the previous researches (Fridley, Zheng, & Zhou, 2008; Jiang & Tovey, 2010; Neto, Augusto, & Fiorelli, 2008), buildings energy consumption account for a significant proportion of carbon emissions.

There are two kinds of understanding about building energy consumption: (i) the building energy consumption of building operation phase, which is internationally accepted definitions and practices; (ii) from the perspective of full life cycle assessment, the energy consumption of building materials production, construction and demolition also take into consideration.

There are many forecasting techniques were used in load engineering (Bianchi, De Santis, Rizzi, & Sadeghian, 2015; Meziane et al., 2016; Miyazaki, Sorensen, Lefebvre, Yum, & Pedersen, 2016; Nguyen, Ve Kifor, & Nguyen, 2016; Ye, Zhuang, Li, & Vigneron, 2016). The software developed quickly in the last couple of years to predict building energy consumption, it includes DOE-2 (York, Tucker, & Cappiello, 1980), ESP-r (Strachan, Kokogiannakis, & Macdonald, 2008), Energy Plus (Crawley et al., 2001), and DeST (Yan, Xia, Tang et al., 2008). Although different kinds of simulation software can be used to predict the building thermal load in many projects (Eskin & Türkmen, 2008; Lam, Wan, Tsang, & Yang, 2008), the simulation results are different of occupied buildings' energy consumption. Because of various parameters setting, the building energy simulation software is too complicated and time-consuming. Some of the more popular of the

* Corresponding author at: Department of Automation, College of Mechanics Engineering and Automation, Shanghai University, Shanghai, China.
E-mail address: jzshilk@126.com (T.-Z. Liu).

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Nomenclature

CL	Cooling load
HL	Heating load
NN	Neural network
BPNN	Back propagation neural network
PSO-NN	Particle swarm optimization neural network
APNN	Autoregressive and particle swarm optimization neural network hybrid model
LSSVM	Least squares support vector machine
PSO-LSSVM	Particle swarm optimization least squares support vector machine
MLR	Multiple linear regression
AR	Auto regressive
ARX	Autoregressive with exogenous inputs
MAPE	Mean absolute percentage error
RMSE	Root mean square error
MAE	Mean absolute error
AE	Absolute error
RE	Relative error
HE	Heat extraction
HS	Heat storage

current building energy simulation software is also difficult to identify the influential variables of building thermal load (Tsanas & Xifara, 2010).Therefore, the research and establishment of a reasonable and effective building load forecasting model that combines indoor/outdoor information and building characteristics has become an important issue to be addressed.

2. Paper review

Estimating the heating or cooling load means to find out what is the power needed by the building in order to maintain the indoor temperature at a desired value when the heat gains and losses vary (Ghiaus, 2013).

The current popular calculation of building energy consumption is to establish a prediction model by available data information of target region and country, the major components of energy consumption is the power needed by the building in order to maintain the indoor temperature at a desired value no matter how the heat changes (Ghiaus, 2013). There are two mainly methods for thermal load calculation: mechanism analysis method and data learning method (Lixia & Tingzhang, 2011). The mechanism analysis method includes thermal response factor method (Mitalas & Stephenson, 1967), Z transfer functions method (Stephenson & Mitalas, 1971), heat balance method (Pederson, Fisher, & Liesen, 1997), radiant time series method (Spitler, Fisher, & Pederson, 1997), state space method (Yan, Xia, Fang et al., 2008), and so on. While the data learning method introduces some advanced control algorithms into room thermal load calculation, such as Auto Regression (Guo et al., 2014), Data Mining (Massana, Pous, Burgas, Melendez, & Colomer, 2017), Grey System (Afram & Janabi-Sharifi, 2015), Artificial Neural Networks (Kumar, Aggarwal, & Sharma, 2013), In Yu et al., classification and regression tree (CART) were used to predict the thermal load of a building with higher precision (Yu, Haghighat, Fung, & Yoshino, 2010). Li et al. make a combination of genetic algorithm and adaptive network-based fuzzy inference system which has been proven to be a well-performance hybrid model (Li, Su, & Chu, 2011). Tsanas and Xifara applied random forest (RF) modeling techniques to predict building thermal load (Tsanas & Xifara, 2012). There are also some other popular forecasting techniques are for forecasting system include general regression neural network (Ben-Nakhi & Mahmoud, 2004),multi-layer neural network system (Kashiwagi & Tobi, 2003),"Regression-Markov" integration model (Korolija, Zhang, Marjanovic-Halburd, & Hanby, 2014), ensemble approach (SVR + ANN) (Chou & Bui, 2014), generalized locally weighted group method (Elattar, Goulermas, & Wu, 2012),hybrid system (Raza, Nadarajah, Hung, & Baharudin, 2017) and so on. Accurate parameters determination and complex calculation procedures are needed in mechanism analysis methods, which is always off-line method for building design and HVAC system installation (ASHRAE, 2013). The data learning based methods always do not distinguish the cooling load and heat extraction, which is ideal condition and suit for energy supply side control (Chabaud, Eynard, & Grieu, 2017; Ji et al., 2016).

Soft sensor technique has already been widely used and plays a more and more important role in the development of modeling and simulating of complex system and control system in recent years. Nowadays, there are many correlated secondary variables of soft sensor for complex objects, which make poor performance, low generalization and bad stability.

Various techniques are used to select influential variables for soft sensors which divide into three groups: filter methods, wrapper methods, and embedded methods. The main influential variables, e.g., relative compactness (Pessenlehner & Mahdavi, 2003), location climate (Wan, Li, Liu, & Lam, 2011), the area of building surface, roof and wall (Schiavon, Lee, Bauman, & Webster, 2010), and window orientation (Parasonis, Keizikas, Endriukaitytė, & Kalibatienė, 2010), should be divided into two aspects: the physical materials of buildings and local meteorological conditions; furthermore, the physical materials can be represented by thermal inertia, which is reflected in the historical thermal loads. These factors make the relationship between Environmental Protection Board (EPB) and its influential variables quite complicated. Thus, accurately predicting the HL and CL of buildings can be a big challenge.

In general speaking, these above methods can be classified as traditional methods based on time series modeling and artificial machine learning techniques and hybrid models of the traditional methods has also achieved effective performances. However, load forecasting is characterized with stochastic properties and strong non linearity. Therefore, a new hybrid model proposed here is supposed to possess a high-level ability to handle the various problems mentioned above.

The above researches underpin that hybrid model has effective performance and better precision in forecasting energy consumption in different kinds of buildings. However, the prediction performance of the aforementioned studies show that hybrid soft-sensor techniques still needs further study, which makes this research more meaningful to make up for the lack of accuracy of single model and in combination with predicting thermal load via soft-sensor measurement validation and multiple performance measures.

In order to address the drawbacks of previous load forecasting models, as presented below, multi-layer hybrid soft-sensor model (APNN) with temperature interval optimized, hybridized with autoregressive exogenous model (ARX) and particle swarm optimization neural network (PNN) can take full use of integrated building load impact factors and achieve higher accuracy in both cooling load and heating load prediction.

3. Model structure and optimization

3.1. Building thermal load formation analysis

The cause of building thermal load formation and mechanism can be classified into two aspects: indoor heating influence and outdoor meteorological conditions impact. Building indoor thermal load mainly originates from electrical work (so called plug load), indoor body heat radiation, among others. These plug load can be foretasted by simplified calculations following the function of heat dissipation. The thermal