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A short-term building cooling load prediction method using deep learning algorithms

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HIGHLIGHTS

- Deep learning-based methods are developed for building cooling load prediction.
- Accurate predictions on 24-h ahead building cooling load profiles are achieved.
- The potentials of supervised and unsupervised deep learning is investigated.
- Features extracted by unsupervised deep learning can improve model performance.
- Supervised deep learning does not show obvious advantages in model development.

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ABSTRACT

Short-term building cooling load prediction is the essential foundation for many building energy management tasks, such as fault detection and diagnosis, demand-side management and control optimization. Conventional methods, which heavily rely on physical principles, have limited power in practice as their performance is subject to many physical assumptions. By contrast, data-driven methods have gained huge interests due to their flexibility in model development and the rich data available in modern buildings. The rapid development in data science has provided advanced data analytics to tackle prediction problems in a more convenient, efficient and effective way.

This paper investigates the potential of one of the most promising techniques in advanced data analytics, i.e., deep learning, in predicting 24-h ahead building cooling load profiles. Deep learning refers to a collection of machine learning algorithms which are powerful in revealing nonlinear and complex patterns in big data. Deep learning can be used either in a supervised manner to develop prediction models with given inputs and output (i.e., cooling load), or in an unsupervised manner to extract meaningful features from raw data as model inputs. This study exploits the potential of deep learning in both manners, and compares its performance in cooling load prediction with typical feature extraction methods and popular prediction techniques in the building field. The results show that deep learning can enhance the performance of building cooling load prediction, especially when used in an unsupervised manner for constructing high-level features as model inputs. Using the features extracted by unsupervised deep learning as inputs for cooling load prediction can evidently enhance the prediction performance. The findings are enlightening and could bring more flexible and effective solutions for building energy predictions.

1. Introduction

The building sector has become the largest energy consumer worldwide, accounting for 32% of global final energy consumption and one third of the Green House Gas emissions [1]. Compared to the transportation and industry sectors, the energy saving potential in buildings is much more significant and could reach 30–80% using currently available building technologies [2]. Among various building services systems, the Heating, Ventilation and Air-Conditioning (HVAC) system is responsible for the largest proportion of building energy consumption (e.g., around 50% in U.S.) and has the largest energy saving potential (e.g., 15–30% for commercial buildings) [3,4]. As a result, the current energy

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conservation measures in building operations mainly focus on the HVAC system. Reliable prediction of short-term (i.e., with a prediction horizon of shorter than 1-week) cooling load profile is the essential foundation for many building energy management tasks [4,5], including optimal control and fault detection and diagnosis (FDD) strategies [6–8]. Ben-Nakhi and Mahmoud adopted artificial neural networks to predict next-day cooling load for optimizing the HVAC thermal energy storage system operation [7]. It was shown that optimal control strategies can increase the operating flexibilities while reducing the operating costs. Lu et al. utilized artificial intelligence for building cooling load predictions with the aim of optimizing HVAC system operations [8]. Energy-efficient operations were achieved by optimizing the set points of chilled water supply temperature, chilled water pump head and supply air pressure in duct networks. Shan et al. developed a robust chiller sequencing control strategy relying on building cooling load predictions [9]. The strategy was validated and could achieve 3% energy saving compared to conventional strategies. Predicted cooling load has been used either directly or indirectly as an indicator for FDD. As examples, previous studies have used cooling load for detecting and diagnosing the low delta-T syndrome in chilling system [10], reducing energy consumption in air-handling units [5], and detecting abnormal energy use at the building-level [11]. Building cooling load prediction is also critical to building demand-side management. A large number of studies have been carried out to investigate the most cost-effective demand response measures (e.g., load shifting) considering the interactions between buildings and smart-grids [6]. An essential assumption of these studies is that reliable predictions of short-term building cooling load profiles are available to use.

Existing methods for short-term cooling load prediction can generally be classified into two types, i.e., physical-model based methods and data-driven methods. Physical-model based methods rely on physical principles and detailed information on building and its systems to characterize building thermal behaviors. The models developed are usually referred as white-box models. Admittedly, they can capture the actual building thermal response to various influential factors, such as outdoor and indoor environment. However, it requires a large amount of detailed building information (e.g., information on building envelop and the selection of building equipment) and the model performance may not be consistent if assumptions of physical principles are not fulfilled [12].

The other type of prediction methods, i.e., data-driven methods, mainly relies on building operational data to discover the relationship between building cooling load and relevant variables (e.g., the outdoor temperature and relative humidity, and indoor occupancy). The models developed in such a manner are known as either grey-box or black-box models [13,14]. The main advantage of data-driven models, especially black-box models, is that the modeling process is more efficient and flexible. The use of advanced data analytics, such as machine learning and artificial intelligence, enables data-driven models to achieve high accuracy and discover potentially useful yet previously unknown relationships with efficient computation. The performance of data-driven methods is mainly affected by two factors, i.e., the prediction techniques used for model development and the features used as model inputs. Previous research showed that the prediction techniques from the field of machine learning and artificial intelligence, such as support vector regression [15,16] and artificial neural networks [17,18], worked very well in building energy prediction. Various studies have also shown that nonlinear techniques could achieve more accurate results compared with linear ones, e.g., multiple linear regression and autoregressive moving average [19,20]. Regarding to the model inputs, previous studies mainly relied on engineering knowledge or simple statistical methods (e.g., correlation coefficient) to select model inputs or develop features as model inputs. For instance, engineering knowledge tells that the building cooling load is closely related to the outdoor weather condition and indoor occupancy. Therefore, outdoor dry-bulb temperature, relative humidity and solar irradiation as well as the indoor occupancy schedule (e.g., *Day of the week*, *Hour* and *Minute*) were typically selected as model inputs [21,22]. Some studies also used historical data as model inputs considering the building thermal capacity [19,23]. Using original historical data, such the outdoor temperature and humidity at previous time steps, as model inputs is generally not recommended, as it may substantially increase the number of model inputs, making prediction models more complicated and computationally expensive. Feature extraction, which transforms raw data into a compact yet information-preserving form, can be applied to develop features as model inputs. Three types of feature extraction methods have been found in previous studies, i.e., engineering, statistical and structural feature extraction [22–27]. Engineering features are constructed based on engineering knowledge and experience, e.g., using the data at previous one-hour as model inputs [23]. Statistical features are constructed using summarizing statistics, e.g., minimum, maximum and mean values of the measurements over a period of time [22,24]. Structural features represent the structural or temporal relationships within the data over a period of time, e.g., the cut-off lag of autocorrelation function or the dominant frequencies in the time-series data [25–27].

The data-driven approaches have gained increasing popularity in the building field, as more and more building operational data are available in modern Building Automation System (BAS). The rapid development in big data analytics offers opportunities for the effective use of big BAS data. One prominent and promising example is deep learning, which has gained huge success in the field of pattern recognition [28,29]. Deep learning refers to a collection of machine learning algorithms which adopts a 'deep' model architecture for knowledge discovery. In other words, the input data will be transformed in either a linear or a nonlinear manner multiple times before deriving the output. By contrast, conventional machine learning algorithms are 'shallow' and input data only undergo one or two rounds of transformation. Deep learning can be used either in a supervised manner for developing a prediction model or in an unsupervised manner for extracting meaningful features from raw data. The former works on two clearly defined data sets as the input set (denoted as X) and the output set (denoted as Y), while the latter works on the input data set (X) alone and aims to extract high-level abstractions of X. Deep learning has demonstrated its power in various applications, such as speech recognition and visual object detection [28,29]; however, it's potential in building cooling load prediction is still unknown. To fill this research gap, this study systematically investigates the potential of deep learning in building cooling load prediction and detailed comparisons with existing analytics are given.

The paper is organized as follows: Section 2 presents the research outline and a brief introduction of data analytics used. Section 3 describes the modeling process using the data retrieved from an educational building. The performance in terms of prediction accuracy and computation load is compared and discussed in Section 4. Conclusions are drawn in Section 5.

2. Research methodology

2.1. Research outline

Fig. 1 presents the general research outline. Feature extraction is firstly carried out to extract meaningful features as model inputs. Four types of feature extraction methods highlighting the unsuper-