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Statistical analysis of energy consumption patterns on the heat demand of buildings in district heating systems

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ABSTRACT

Precise prediction of heat demand is crucial for optimising district heating (DH) systems. Energy consumption patterns (ECPs) represent a key parameter in developing a good mathematical model to predict heat demand. This study quantitatively investigated the impacts of ECPs on heat consumption. Two key factors, namely, time and type of buildings, were used to reflect various ECPs in DH systems, and a Gaussian mixture model (GMM) was developed to examine their impacts on heat consumption. The model was trained and validated using the measured data from a real DH system. Results show that the factor of time does not represent a good reflection of ECP. In contrast, categorising buildings according to their function is an effective way to reflect ECPs. Based on the defined building types, i.e., commercial, apartment and office, the average absolute deviation of the predicted heat load was about 4–8%.

1. Introduction

According to the European Environmental Agency (EEA), the heating and cooling sectors are the main players in the European energy market, responsible for more than half of the total final energy consumption and a significant share of European greenhouse gas (GHG) emissions [1]. District heating (DH) is the most efficient option for space heating and thus is considered an important solution to the EU's ambitious climate and energy 20–20–20 target, i.e., a 20% reduction in EU GHG emissions from the 1990 levels. It was estimated that DH could help Europe reduce total European CO_2 emissions by 9.3% by 2020 [2].

There have been many studies aiming to optimise the overall performance of DH systems, and heat demand is a key parameter in these studies [2]. Some studies, for example, have focused on the dynamic simulation of DH networks in order to understand the performance of DH in combination with production planning and optimization [3–7]. Other research has looked into how pumping work can be saved at part-loads by, for example, replacing conventional central circulation pumps with distributed variable speed pumps [8–11]. Heat demand was commonly used as a key parameter in all of these studies.

Physically, heat demand is determined by ambient temperature, indoor temperature, building materials, construction structure, and weather conditions etc. Many models have been developed based on the correlations of heat transfer [12–18]. In addition, heat demand is also closely linked to the characteristics of energy consumption patterns (ECPs), such as different functions of buildings and different lifestyles, which are difficult to describe in mathematical equations. Some statistical methods have been developed to predict energy demand, and these methods are strongly dependent on historical data [19–22]. For example, Yao and Steemers [19] proposed a statistical method of formulating load profile, which integrates a thermal dynamic model and a statistical model, to predict daily energy demand load profile from individual house to urban community. Nielsen and Madsen [20] presented a grey-box model for predicting the heat consumption in a large DH system based on time-series data about climate.

Many regression models have been developed to consider the impacts of ECPs on energy demand. Jónsson [21] presented a model that could predict the yearly load of a DH system, and the number of houses, the climatic impacts and the behaviour of consumers were

Abbreviation: AB, apartment building; AD, absolute deviation; CB, commercial building; DH, district heating; ECP, energy consumption pattern; EEA, European Environmental Agency; GH, Ggreenhouse gas; GMM, gaussian mixture model; OB, office building; PDF, probability density function.

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x^h	heat demand
x^o	outdoor temperature
$\boldsymbol{x}$	two-dimensional vector contains x^h and x^o
$f(x)$	probability density function of $\mathbf{x}$
c_i	mixture weight for the ith mixture component
μ_i	mean of the ith mixture component
Σ_i	covariance matrix of the ith mixture component
μ_i^h	mean of heat demand in the ith mixture component
μ_i^o	mean of outdoor temperature in the ith mixture component
σ_i^h	standard deviation of heat demand in the ith mixture component
σ_i^o	standard deviation of outdoor temperature in the ith mixture component
$\sigma_i^{ho}, \sigma_i^{oh}$	cross covariance between σ_i^h and σ_i^o
$\hat{x}^h$	predicted heat demand
Subscript	
i	ith mixture component
t	time point

considered in the model. Dotzauer [22] constructed a model based on the premise that heat demand is affected by outdoor temperature and different consumer behaviours, which are tightly related to the time in a day. Generally speaking, it is a common way to use the factor of time to reflect ECP in existing models, such as the model developed by Yao and Steemers [19] and Dotzauer [22]. However, the effects of the factor of time have so far not been quantitatively examined in existing studies especially in a quantitative way.

In addition, ECPs are also tightly related to the type of buildings. Previous research investigated the heat demand in a specific type of buildings, such as residential buildings, office buildings and commercial buildings [23–26]. A common conclusion that can be drawn from these studies is that the heat demand in different types of buildings varies significantly. However, there have been only few studies that systematically examine the relationship between building types and heat consumption. Barelli et al. [27] proposed a new method to simulate the daily and hourly trend of thermal load, and the model was adopted to simulate two buildings, namely a school building and a residential building. However, the model was validated only using seasonal data and there was no further analysis on how building types would affect heat demand.

In order to develop a good mathematical model that can accurately predict heat demand on a daily base, or even on an hourly base, it is essential to understand the impacts of ECPs and properly describe them in the model. Therefore, this study aims to quantitatively investigate the impacts of ECPs on heat consumption. A Gaussian mixture model (GMM) was developed to predict the heat consumption of a DH system according to various ECPs. Two key parameters, namely the factor of time and building types, were used to reflect various ECPs in DH systems. The model was trained and validated using the measured data from a real DH system. In addition, the GMM was further adopted to estimate the potential energy reduction achievable from the savings of pump work in the DH system. Finally, the insights on modelling heat consumption according to ECPs were summarised to conclude the study.

2. Methodology

A GMM is used as the fundament for the development of the heat demand model. According to the central limit theory, the measurements of many properties are often Gaussian distributed [28]. In the case of heterogeneous populations, data measurements often present a mixture of Gaussian distributions. Therefore, GMMs can be used to predict heat demand. Using GMM [29], a widely used technique in machine learning, can effectively discover the relationship between heat demand and outdoor temperature by modelling their joint distribution.

The historic data about water flow rate, temperatures of supply water and return water, ambient temperature, and heat consumption were used for both model training and validation. To reflect the ECPs using building types, the buildings were divided into three types according to their functions, namely commercial buildings (CB), apartment buildings (AB) and office buildings (OB). In addition, the measured data were grouped into different time periods according to different partition strategies in order to take the effects of time into consideration.

3. Measured data

The measured data used in this study were obtained from a DH system in Jinan, the capital city of Shandong Province, China. The total area covered by the DH system is around 70 million m^2. Table 1 shows the general information on a sample building of CB, AB and OB, which was measured hourly from November 20, 2012 to February 5, 2013. Note that the three buildings have a similar physical area.

The consumption patterns of the three types of buildings are illustrated in Fig. 1, which shows their heat demand during the period from December 28, 2012 to January 3, 2013. Although the heat demand of the three buildings varied according to the ambient temperature, their variations exhibited different patterns. Of the three buildings, the CB had the largest heat demand, and it fluctuated most significantly from time to time. This is due to the relatively large heat loss in the CB, because of the greater number of entrances and exits, as well as a fluctuating number of customers. In contrast, the AB consumed the least amount of heat of the three buildings, largely due to the low level of ventilation. These observations indicate that building type has a significant impact on heat consumption.

In addition, heat consumption depends on several factors. For example, when the ambient temperature falls, heat consumption will increase to keep the indoor temperature stable. This increase in heat consumption is met by coordinating the temperature of the supply/return water and the water flow rate. Fig. 2 displays the temperatures of supply/return water and the water flow rate of the CB during the period 28 December 2012 to 3 January 2013.

4. Model development

4.1. Model description and training

From a statistical point of view, heat demand and the factors that influence heat demand are highly correlated. In order to capture the correlation, the observation vector, which contains the measured data, is assumed to be Gaussian distributed. This assumption not only follows the central limited theory, but also explicitly captures the correlation between the factors in the observation vector.

Denote the observation vector as $\mathbf{x} = [x_1, x_2, \ldots, x_K]^T$, where x_i is heat demand and x_k, $k = 2, 3, \ldots, K$ denotes other factors mentioned above (assuming that $K - 1$ factors that affect heat demand are available). Thus, the probability density function (PDF) of a single Gaussian distribution is:

$$N(\mathbf{x}; \mu, \Sigma) = \frac{1}{\left(\sqrt{2\pi}\right)^K \sqrt{|\Sigma|}} e^{-\frac{1}{2}(\mathrm{x}-\mu)^T \Sigma^{-1}(\mathrm{x}-\mu)}. \tag{1}$$