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Validation of a community district energy system model using field measured data

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ABSTRACT

Load prediction is the first step in designing an efficient community district heating system (CDHS). Even though several methods have been developed to predict the heating demand profile of buildings, there is a lack of method that can predict this profile for a large-scale community with a numerous user types in a timely manner and with an appropriate level of precision.

This paper, first briefly describes the 4-step procedure developed earlier, utilizing a Multiple Non-Linear Regression (MNLR) method, for predicting the heating demand profile of district, followed by description of the community structure, and its district system. It also reports the field measurement procedure for collecting the data required and the preliminary analysis data. Results obtained from a continuous monitoring of the CDHS over a two-year period is employed to validate the accuracy of the developed model in the predicting the CDHS's heating load profile. Finally, using the 4-step procedure, the district's energy demand profile is predicted, and compared with both the measured data and the initial prediction. The outcome shows a less than 11.2% in the mean square root error (MSRE) of the predicted and measured load profiles.

1. Introduction

Providing secure and clean source of energy to respond the households' demand is one of the upmost fundamental challenges faced by the energy planners. In effect, households represent a significant share of the total energy demand; they are responsible for 40% and 26% of the total energy consumption in North America and Europe, respectively [1]. In the last few decades, using fossil fuels as the world's main energy source has resulted in their depletion and increased the level of CO_2 equivalent emissions. There are targets for reductions in CO_2 emissions worldwide. Specifically, the Energy Technology Perspective 2012 Roadmap (IEA) aims to reduce CO_2 emissions by 50% [2]. Given the expected rise in household energy consumption, the building sector is now required to adapt to the new ambitious demands of developing Net-Zero Energy Buildings/communities (NZEB) by 2050.

Numerous building energy conservation strategies have been tested using energy storage [3–5] and user-demand [6] methods. The Hybrid Community-District Heating System (H-CDHS) is a unique energy management alternative given its storage and renewable systems are integrated in the district's thermal energy system. Since the energy generated by renewable sources is not uniform throughout the day, a thermal energy storage unit allows the system to synchronize with the supply and demand. To implement this system effectively, it is essential to predict the H-CDHS′ detailed energy demand profile [7].

Hence, several methods have been developed to model buildings' energy demand profile [8–10]. Given its restricted number of users, a small-scale H-CDHS energy demand profile can be predicted using a detailed model of users' consumption created with energy simulation models [8]. Conversely, in large district scale systems, due to the large volume of users, a comprehensive modeling is time-consuming, computationally expensive and sometimes impractical. Some researchers used comprehensive models to predict the heating demand profile of larger scale communities [11,12]. To overcome this problem, variety of simplified models were developed to predict the heating demand profile or total energy demand of large communities. These simplified models could be divided into four major categories—black box

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models (e.g. ANN) [13]; gray box models [14,15]; equivalent RC networks [16–18]; and regression models [19–24]. Regardless of the method chosen, previous demand estimates focused mainly on predicting the peak and total energy demand. Only few studies tried predicting the demand profile [11,14,23].

Though these simplified models could reduce the computational time to a fraction of that of comprehensive models, their simplicity would compromise the prediction accuracy due to limitation of the simplified models. Three major drawbacks could be assumed for most of these simplified modes. First, the low prediction accuracy emerging from assumptions made in modeling the individual buildings/units a) presentation of the occupants' behavior and, b) the interaction of each building with surrounding buildings in an urban setting. One of the most challenging issues of heating demand prediction models is having to correct input parameters. Input parameters that are dependent on occupants' behavior/activities, including heating set points and schedules; Internal heat gain due to occupants' activity and the building's heating system; natural ventilation flow rate; solar gains from using windows blinds or shades, etc. Second, scaling effects impair accuracy by oversimplifying scaling methods that extrapolate results from building level to the district level. And third, flexible methods that predict community load profile in diverse building types. More details regarding the limitation of previous projects can be found in previous works done by authors [8,25]. Table 1 summarizes studies related to CDHS′ heat demand prediction. A closer analysis of existing models reveals that the current scholarship requires further validation of models that predict heating demands using measured data.

This paper endorses a 4-step procedure developed to predict the energy demand profile for H-CDHS. It, first briefly describes the 4-step procedure [25] developed earlier for predicting the heating demand profile of district, followed by description of the community structure, and its district system. It also reports the field measurement procedure for collecting the data required for validating the model from the West Whitlawburn Housing Co-Operative (WWH) CDHS in Scotland. The measurement technique, and the preliminary analysis data are explained. Finally, using the 4-step procedure, the district's energy demand profile is predicted, and compared with both the measured data and the initial prediction.

2. Methodology

2.1. The four-step demand profile procedure

Talebi et al. [25] developed a simplified model to predict the heating demand profile and peak loads in complex district systems. Fig. 1 shows the procedure used in the development of the simplified models. The procedures are based on the Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MNLR) methods. In this four-step procedure, the entire district's heating demand profile is predicted by modeling each individual unit in the community using its physical and geometrical characteristics, the regions' meteorological information, and the occupants' general behavior.

1) In the first step, a sample building stock model (BSM) is segmented into different archetypes, and a reference building is defined for each archetype. The initial segmentation is completed by considering the building's construction method, physical and geometrical properties, and construction period [25]. Once the initial archetypes are determined, each archetype is further divided into sub-archetypes based on the occupancy schedule (e.g. residential user with high, medium and low usage, etc.) of the building within that archetype. Different methods are used for segmenting the BSM based on the occupancy schedule. While some researchers only segment the BSM based on major occupancy types (e.g. residential, commercial, or office types), others segment it following the user's energy profile. This study presents a more detailed approach for defining the number of archetypes as well as the reference building for each archetype. A hierarchical clustering method was adopted for this end. In this method, the data set is split into a prefixed number of clusters. The building closest to the centroid of that cluster is defined as a reference building for that

Table 1
Load prediction summary.

Author	Ref	Year	Prediction period	Prediction Type/Resolution	Method
Fonsenca et al.	[26]	2015	Annual	Total Energy Demand	Simplified Modeling/Adjusted HDD
Powell et al.	[13]	2014	Daily	One day forecasting	NARX**; ANN
Tuominen et al.	[19]	2014	Annual	Total Energy Demand	Linear Development Using REMA
Filogamo et al.	[16]	2014	Annual	Total Energy Demand	Simplified Equivalent RC
Koene et al.	[17]	2014	Annual	Total Energy Demand	Simplified Equivalent RC
Gadd et al.	[27]	2013	Daily	Average Daily and Hourly Variation	Time Series
Caputo et al.	[28]	2013	Annual	Total Energy Demand	Comprehensive Modeling
Nouvel et al.	[29]	2013	Annual	Total Energy Demand	Quasi State Monthly Energy Balance
Galante et al.	[20]	2012	Annual	Total Energy Consumption	Linear Regression Analysis
Ali et al.	[30]	2011	Annual	Peak Load and Total Demand	Multivariant Regression
Lee et al.	[15]	2011	Annual	Total Energy Demand	Gray Box Model
Theodoridou et al.	[12]	2011	Annual	Annual Peak Demand	Comprehensive Modeling
Goia et al.	[31]	2010	Monthly	Peak Load Forecasting	Linear Regression & Clustering
Mavrogianni	[21,24]	2009	Annual	Annual Heating Degree Day	Linear Regression
Linda Pedersen et al.	[22]	2008	Annual	Linearized peak Day Profile*	Linear Regression
Ihara et al.		2008	Annual	Total Energy Demand	Gray Box
Heiple et al.	[11]	2008	Annual	Hourly/Total Energy Demand	Software Modeling, "eQUEST"
Nielsen et al.	[14]	2006	Annual	Profile	Gray Box
Tanimoto et al.	[32]	2008	Annual	Peak Demand	Stochastic method
Koroneos		2005	Annual	Total Energy Demand	Gray Box
Ratti et al.		2004	Annual	Total Energy Demand	Multivariant Regression
Shimoda et al.	[33]	2004	Annual	Total EUI/Total Energy Demand	Software Modeling, "SCHEDULE"
Eicker	[18]	2004	Annual	Total Energy Demand	Simplified Equivalent RC
Dotzauer	[23]	2002	Annual	Profile	Linear Regression

**NARX: nonlinear autoregressive network with exogenous inputs.