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Model for forecasting residential heat demand based on natural gas consumption and energy performance indicators

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HIGHLIGHTS

- Analysis of historical data of hourly natural gas consumption for town-level aggregation.
- Characterization of correlations and discrepancies between natural gas demand and outdoor temperature.
- Development of a model of hourly gas consumption for heating purposes.
- Definition of an hourly forecasting model for buildings' heat demand based on Italian energy labels.

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ABSTRACT

The forecasting of energy and natural gas consumption is a topic that spans different temporal and spatial scales and addresses scenarios that vary significantly in consistency and extension. Therefore, although forecasting models share common aims, the specific scale at which each model has been developed strongly impacts its features and the parameters that are to be considered or neglected. There are models designed to handle time scales, such as decades, years, and months, down to daily or hourly models of consumption. Similarly, there are patterns of forecasted consumption that range from continents or groups of nations down to the most limited targets of single individual users, passing through all intermediate levels. This paper describes a model that is able to provide a short-term profile of the hourly heat demand of end-users of a District Heating Network (DHN). The simulator uses the hourly natural gas consumptions of large groups of users and their correlation with the outside air temperature. Next, a procedure based on standards for estimating the energy performance of buildings is defined to scale results down to single-user consumption. The main objective of this work is to provide a simple and fast tool that can be used as a component of wider models of DHNs to improve the control strategies and the management of load variations. The novelty of this work lies in the development of a plain algebraic model for predicting hourly heat demand based only on average daily temperature and historical data of natural gas consumption. Whereas aggregated data of natural gas consumption for groups of end users are measured hourly or even more frequently, the thermal demand is typically evaluated over a significantly longer time horizon, such as a month or more. Therefore, the hourly profile of a single user's thermal demand is commonly unknown, and only long-term averaged values are available and predictable. With this model, used in conjunction with common weather forecasting services that reliably provide the average temperature of the following day, it is possible to predict the expected hourly heat demand one day in advance and day-by-day.

1. Introduction

Natural gas (NG) demand for residential and commercial use in buildings was approximately 31% of the total gas demand in 2011 in the US [1] and approximately 25% in Italy [2]. Currently, the reduction of consumption comes from the application of best and updated design practices, as well as from managing the demand and its variation in time and intensity. For this reason, there have been a large number of papers in recent years that address models that aim to predict the production, delivery and consumption of energy and NG [3].

The various models differ one from one other in the reason that they were built, which, in turn, is strictly linked to the extension of

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Nomenclature

c_h	dependent point regression coefficient	HDD_{real}	measured heating degree day [°C day]
$D_{build,h}$	building's hourly heat demand [kWh/h]	HSAD	Hot Season Average Demand [kWh/h]
$D_{build,year}$	building's annual heat demand [kWh/year]	K	scaling and conversion coefficient [kWh/Sm^3]
DHN	District Heating Network	NG	Natural Gas
DHOff	Daily Heating Power Off period	NGD	Natural Gas Demand
DHOn	Daily Heating Power On period	NGD_h	hourly natural gas demand [Sm^3/h]
DHW	Domestic Hot Water	NGD_{year}	town's annual natural gas demand [Sm^3/year]
EP_{Li}	Energy Performance Indicator Limit	p_1	main point's linear regression coefficient [Sm^3/h °C]
ET	Environmental Temperature [°C]	p_2	main point's linear regression coefficient [Sm^3/h]
$\overline{ET_d}$	average daily environmental temperature [°C]	SHOff	Seasonal Heating Power Off period
HDD	Heating Degree Day [°C day]	SHOn	Seasonal Heating Power On period
HDD_{law}	indicated heating degree day [°C day]	S/V	building aspect ratio [1/m]

the scale and time-scale of the model itself. Some models address global and national levels, such as [3–6] with timescales of years or decades; many models are devoted to directly predicting natural gas consumption at the hour and city level [4], while others address the yearly and national scale [5] or daily predictions at the town level [6].

The forecasting of heating energy demand and consumption is assessed in several ways by a number of authors (see, e.g., the reviews of Swan and Ugursal [7], Suganthi and Samuel [8] and Kramer et al. [9]). Artificial neural networks (ANNs) and fuzzy systems are used by Neto and Fiorelli [10], Li et al. [11,12], Yang et al. [13], Ekici and Aksoy [14], and González and Zamarreño [15]; ANNs are easier to use compared to statistical methods and, for forecasting problems, are usually used in conjunction with back propagation (BP) learning algorithms, but their learning approach is nevertheless of a black box style. Moreover, it is difficult to address uncertainties and understand dependencies between inputs and outputs.

Strzalka et al. [16] used a 3D city model, interfaced with either a transmission-loss model or an energy-balance model, to forecast the heating energy demand of an entire city quarter. They underline that building simulation models typically require such a high amount of input data that it is often hard to acquire. Yu et al. [17] used a decision tree method, whose flowchart-like tree structure enables users to quickly extract useful information without requiring much computational knowledge. Effective energy consumption (in accordance with CEN-Umbrella prEN 15603 Clause 7 [18]) is used by Tronchin and Fabbri, and compared with results obtained by well-established simulation software [19]. They underline the high peculiarity of the Mediterranean climate that have to be taken into account when approaching this type of problem in this particular region. Finally, some authors, such as Široký et al. [20] and Oldewurtel et al. [21], have proposed model predictive control methods that aim to minimize the energy consumption by means of advanced control techniques, whose accuracy is nevertheless influenced by the intrinsic uncertainty of weather data, which is used as an input.

Nannei and Schenone [22] developed and experimentally validated in a real-scale climatically controlled test room a numerical model to study thermal transients in buildings, which is useful for both evaluating heating energy consumption and achieving conditions of environmental comfort.

Jain et al. [23] developed a building energy forecasting model using support vector regression to describe a multi-family residential building in New York City. They found that "Optimal granularity occurs at subdivision at floor level, in hourly temporal intervals," and their results indicate that the most effective models are built with hourly consumption at the floor level.

Liu et al. [24] addressed forecasting for electrical consumption: their hybrid model aims to predict hourly consumption in microgrids, and the authors stated that research on this topic is still currently limited, partly because aspects of these research studies have high computational complexity. Richardson et al. [25] and Widén et al. [26] also forecast building electrical consumption, looking at the human occupancy and the activity of people, as well as at the appliances that people use in their activities.

Fan et al. [27] used a data mining approach to spot the six most relevant independent variables for next-day building energy consumption and peak power demand.

Olofsson and Mahlia [28] presented a methodology, based on a simulation module and graphical figures, for interactive investigations of building energy performance using the improved procedure of the EN 832:1998 standard [29] to calculate the heat loss through the floor and the solar heat gain.

Pisello et al. [30] proposed a new methodology for the evaluation of buildings' thermal-energetic performance that allows the translation of dynamic simulation results into buildings' energy guidelines.

Braun et al. [31] used regression analysis to predict future energy consumption of a supermarket, while Lee and Tong [32] used a hybrid dynamic model to forecast nonlinear time series of energy consumption.

Yao and Steemers [33] used a simple deterministic method to develop a realistic energy profile for a flat that takes into account each device and activity in a flat to build up a realistic load profile.

Analogously to what was explained for residential heating energy demand, almost the same techniques can be used to forecast natural gas consumption, and the most common are linear regressions [34,35], nonlinear regressions [36,37], autoregressive time-series models [38], artificial neural networks [39,40], genetic fuzzy systems [41] and logistic-based approaches [42].

In particular, Potočnik et al. [43] investigated the performance of static and adaptive models for short-term natural gas load forecasting, showing that the improvement of the forecasting performance due to adaptive models does not appear for an individual house due to the stationary regime of its heating.

Sabo et al. [4] created an hourly forecast model based on short-term temperature variation and gas consumption in the preceding period that considers the "variation of consumption" as a relevant parameter and recognizes the temperature as the main independent variable.

Brown et al. [44] used an econometric approach to find the weight of the parameters involved in gas consumption; the model uses two different HDDs in the same expression, calculated with two different reference temperature values, and it also considers the effect of NG price on consumption.