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

Many authors use the Heating Degree Day (HDD) to forecast gas consumption, and some of them define corrections [45] or weights [46] for the value of HDD to produce more reliable predictions.

The most detailed review of NG forecasting models can be found in [3]; it contains an extensive analytical classification of those available in the literature.

Taking into account the lessons learned from the papers described in the literature survey examined above, the advantages and disadvantages of each simulation technique, the available inputs, and the needs in terms of time scale, physical accuracy and simplicity, the authors developed the model that is described in this paper.

The large number of papers and models available in the literature illustrates the large interest in the forecasting of energy demand. Indeed, one can use the model, which uses a set of simple equations to describe the spatial and temporal distribution of a building's energy demand, as one of the key components to develop wider dynamic models, such as ones for District Heating Networks (DHNs).

A DHN connects users and thermal production units, which could be located afar, provided that they are all connected to the network. This allows considerable technical advantages, for instance, the exploitation of low enthalpy sources and renewables, as well as the possibility of moving the production units and thermal storage to less densely populated areas.

The design of a DHN is based on the following features of the users' thermal energy demand:

- the power demand peak
- the geographical location
- the daily and hourly profile of energy demand.

The energy demand peak is required to define the size of the system; the distribution of the demand is needed to determine the best shape of the DHN that complies with the energy demand of single users or that of a district. Finally, the seasonal and hourly trends of energy demand play a key role in maximizing the share of renewable energy by means of thermal energy storage.

For these reasons, a model of hourly heat demand for a generic building is useful for defining effective strategies aimed at integrating users and suppliers based on spatial and temporal mapping of the city's thermal demand.

This paper describes the procedure used to create the model that estimates the hourly profile of the thermal demand of a building. The needs of creating a reliable model, based on a large set of measurements, led the authors to take two sets of data into consideration. The first set is a decade's-worth of hourly consumptions of natural gas of the entire town, which are collected and recorded at an hourly frequency or higher, and it was made available thanks to the collaboration with the local NG delivery company. The second one is the annual consumption for heating of buildings that can be obtained by direct measurements, which are not available at an hourly frequency and are measured once a month (or less). In cases in which the annual consumption of a building is not available, the procedure illustrates how to use the Energy Performance Indicator of Building to evaluate the proper scaling and conversion factor from aggregate hourly gas consumption data to a single user's hourly heat demand.

The main improvement of this method is that it provides a simple and fast tool that can be used as a component of wider models of DHNs to improve the control strategies and management of load variations. In fact, more sophisticated models often clash with the lack of data or with their gross uncertainty, while the present approach can be applied to a number of real situations with an actual expectation of achieving operative results. Hence, the proposed model is particularly useful when energy planning for a large number of end users is needed and when it is necessary to assess energy demand at a district or city level, as for the Sustainable Energy Action Plan foreseen by the Covenant of Mayors [47]. The developed tool seems to be particularly adequate for that purpose.

A further advantage is the possibility of recognizing and understanding the effects of external temperature and the habits of users on trends of energy demand over time. Indeed, in comparison with more sophisticated and mathematically complex methods, which give more accurate predictions, the use of simpler functions makes it easier to distinguish the different effects mentioned above. Whereas aggregated data of natural gas consumption for groups of end users are usually measured hourly or even more frequently, the thermal demand is 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, one day in advance and day-by-day, the expected hourly heat demand.

Moreover, the simplicity of the model facilitates its use and dissemination. The proposed approach can be adopted in several diverse contexts and applied with good flexibility, as it has been for the CELSIUS consortium [48], which included it in the CELSIUS toolbox and recommended it to the follower cities, i.e., the cities that expressed their willingness to replicate the actions of CELSIUS demonstrators, as a meaningful forecasting method.

The research activity was developed in two steps. The first one is represented by the group of actions that were undertaken to define the pattern recognition of the daily profile of NGD by means of the analysis of hourly consumption aggregated for a large numbers of users. The second part concerns the method by which it is possible to use the normalized NGD profiles to forecast the details of the hourly heat demand of users, starting from data of annual heat demand. The paper was developed in the context of Covenant of Majors and Celsius Project research studies.

2. Natural gas distribution and consumption in Genoa

Several gas networks commonly coexist in urban areas. These networks commonly differ from one other in pressure level, in their number and in the diffusion of their branches. In a typical configuration, there are three networks at three different pressure levels: the high pressure network at 70–25 bar_g, the intermediate pressure network at 5 bar_g and the low pressure network at 1.5–0.5 bar_g which feeds the last pressure jump cabins, which deliver gas to users at 0.05 bar_g. The connection between the networks is provided by the NG expansion facilities.

The city of Genoa, as in the majority of urban agglomerations in Italy, is provided with an extensive NG distribution network. In Genoa, there are seven main expansion cabins, twenty secondary expansion plants and a couple hundred low-pressure expansion facilities. The first jump cabins reduce the NG pressure from the national distribution level (24–26 bar_g) to medium pressure (5 bar_g); the second ones are widespread in the city and reduce the pressure levels from 5 to 1.5–0.5 bar_g. Finally, the lower pressure expansion cabins serve less than a thousand end users each.

NG is a strategic energy source for Genoa; in fact, most of the residential units are connected to the distribution network; the fuel is mainly used by citizens for cooking, heating and Domestic Hot Water (DHW) purposes.

The NG industrial demand is very low in the city, and in recent years, it has really decreased. That is why most of the consumptions, which take place in the heating period, are directly linked to the heating of buildings.

The Italian rules for energy savings for buildings [49] subdivide the country into climatic zones on the basis of a HDD (Heating Degree Days) classification. For each zone, the law defines many parameters regarding the minimum thermal performances of the buildings and the extension of the periods in which it is possible to activate heating systems.

The town of Genoa is classified in the zone "D", where houses can be heated, unless there are specific exceptions, from November 1 through April 15. This period is called the Seasonal Heating Power On period (SHOn). In the SHOn period, the conventional heating devices can be switched on, starting from 05:00 to 23:00, for less 12 h per day [50]. This interval is called the Daily Heating Power On period (DHOn).

3. Methodology

As previously said, this work consists of two main steps. The first one is the development of the model for forecasting the town's NG Demand (NGD) from its correlations with the average daily temperature: the analysis of data revealed a direct correlation between the outside-air temperature and the NG consumption during six pivot hours of the day in any day of the heating period.

In the second step, a simple method for scaling the results to estimate the building's hourly heat demand is described. This model has been used to predict hourly thermal demand, days in advance, based on the forecast of daily average temperature.

The development of this procedure stems from the wish of addressing the need of a simple and easily adaptable model for the forecasting of NGD and that, thanks to the collaboration with the local gas distribution company, it was possible to have available and to analyse a large set of hourly NG consumption data of the entire city. Hence, the model was thought to utilize aggregated data of NG consumptions of a wide group of people (such as an entire city or a large district) to predict the profiles of heat consumptions of a restricted group of users, or even of a single user.

The main steps of the methodology are the following:

- Data collection: the forecasting process uses two sets of data. The first set consists of aggregated NGD data, over a significant number of years, gathered for a large geographical area and a great number of final users; the second one is the daily average of ET for the same location and period.
- Data cleaning: a conventional data cleaning process, for NGD and ET data, targeted to eliminate errors, false zeros and malfunction of the measuring system.
- Data pre-processing: this process is aimed to split the aggregate NGD data on the basis of its final use, and the process is closely related to the marked seasonality of consumption and of NG consumption habits. We can assume that NGD is made up of two main terms: a share of consumption linked to habits that do not vary throughout the year and a share related to the demands of heat that, as well as being linked to the habits, are closely correlated to the value of the daily average outdoor temperature. A simple way to find the part of the NGD that is linked exclusively to the request of heat is to clean the bulk data with that of the summer months in which the required heat is negligible.
- Correlation between NGD and ET: this step consists of the examination of the NGD hourly profiles to pick out simple mathematical functions that could be able to describe the correlation between NGD and ET with ease of replication and good accuracy. The observation of the daily distribution of NGDh leads to the identification of, for short segments of time of day, consumption profiles that can be represented by simple functions. The selection of the proper extension of the intervals consists of a "trial and error" activity, and the main point of a time band is the one that shows the strongest cross correlation with the daily average of the external temperature. The result of this data analysis process, carried out in collaboration with the local NG delivery company, leads to a model that describes with high detail over time (hourly or sub-hourly intervals) the consumption pattern of a very broad set of users.
- Final user hourly heat demand: the patterns of consumption are strictly linked to the habits of the users. For this reason, they can be used to calculate the hourly consumption of a single user or of a restricted set of users (e.g., a small district), of which the hourly consumption is generally not measured and the data of consumptions are available over long periods only (measured monthly or seasonally).

The way in which it is possible to use a set of readily available data, such as the pattern of consumption, the value of HDD in the investigated period and the daily average ET, to define the hourly consumption of a single user is described in Section 5.

Finally, Section 6 describes the procedure to estimate the hourly consumption in the case in which the monthly (or yearly) consumption is unknown, and it is evaluated by means of Ep_i, which represents an estimation of the annual energy consumption as a function of HDD and the building energy label in combination with the model presented in this paper.

4. Data analysis

Thanks to the collaboration with the local NG delivery company, it was possible to analyse the hourly consumption of the entire town for a decade. At first, the analysis of these data was accomplished with the aim of looking for correlations between the daily averages of consumptions and temperatures. Then, such a large set of data, which describes the details of consumption during the whole year, has been used to deduce a model of hourly consumption for the heating period.

Firstly, the correlation between NGD and Environmental Temperature (ET) has been studied at a monthly scale. The monthly averages for NGD and ET are reported in Figs. 1 and 2, respectively. It is possible to observe that the NGD is only slightly affected by the ET during the Seasonal Heating Power Off period (SHOff) because the NG is mainly used for cooking and for DHW. Thus, the energy demand is lower than 20% of the maximum demand needed in winter, and the correlation between the two variables is very poor. Alternately, the maximum values of NGD take place in the Seasonal Heating Power On (SHOn) period.

Looking at the monthly averages of NGD and ET, Figs. 1 and 2, it can be observed that small changes in ET result in considerable variations of NGD during the transitions from heating periods to non-heating ones. In this case, the relation between the variables is determined by citizens' uses of the NG, and it is possible to

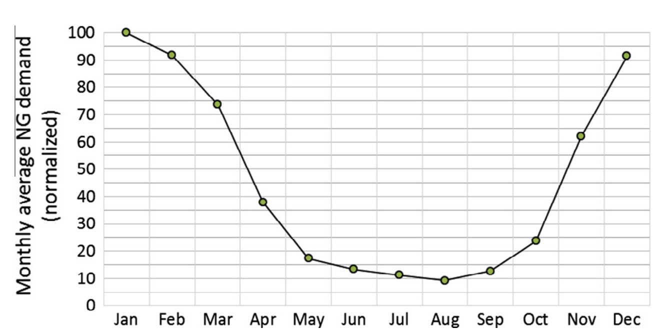

Fig. 1. Monthly average NGD (normalized).

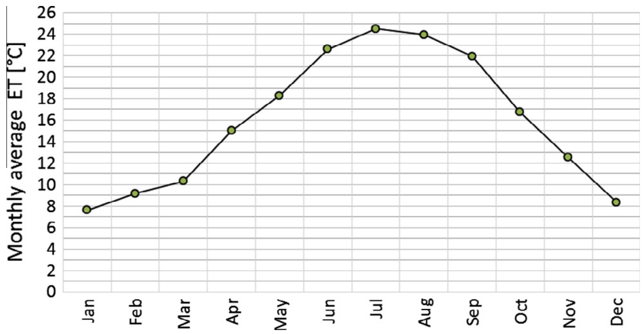

Fig. 2. Monthly average ET [°C].

deduce that, during the SHOn period, most of the NG consumption is used for building heating purposes.

It is possible to gain a different point of view by looking at plots of the two variables on a daily basis. The graphs in Figs. 3 and 4 show hourly average values of NGD and ET, respectively, for each month of the year. The synoptic analysis of the two pictures clearly shows the effect of the external temperature together with the effect of the duration of the daily heating interval (DHOn).

Though NGD profiles of the cold months significantly differ from those of the hot months, they are always characterized by a well-defined pattern with three peaks of gas demand at 07:00, 12:00 and 19:00. In these cases, there is not a direct correlation between the hourly profile of ET behaviours and the hourly NGD profile. This is a combined effect of multiple causes:

- *Physical* ones: the building forms a complex thermal system in combination with the environment. The thermal inertia of the building decouples the heat losses from the heat needs, producing a delay from the variations of ET and NGD.
- *Anthropogenic* ones: as has been previously described, the result comes from a mixed effect of rules and habits. The Italian law imposes a specific DHOn period, and for this reason, people commonly shut heating down during night; even if ET decreases, there is not a corresponding increase of NGD. During the DHOn hours, every user can choose to switch on or switch off its heating devices; most people switch on boilers early in the morning and at dinner time when most people are at home. These habits are responsible for the peak of NGD at 7.00, for the narrow peak at lunch time, which is strongly related to the gas that is used for cooking lunch, and for the smoother and wider peak at 7.00 pm, which is a combination of heating and cooking.

5. Model for forecasting natural gas demand at the town level

At this stage, the main purpose of this study is building a model that is able to predict the gas demand linked to residential and commercial hourly heat demand. It is worth recalling that the available data are the gross NGD values, including gas for cooking and DHW, extended to the entire city of Genoa.

On the basis of the previous considerations, a preliminary analysis has been performed to single out the contribution of the cooking and DHW gas demand.

The main assumption is that the NG demand, in the SHOff period, is mainly due to cooking and that there are not significant variations of this term throughout the year. For this reason, it is possible to evaluate gas consumption for heating demand, in the SHOn period, by subtracting the average hourly demand in the SHOff period, defined as the Hot Season Average Demand (HSAD), from the gross value recorded by the meters. A general NGD daily trend for the SHOn period, cleaned by the HSAD values, is shown in Fig. 5; the net profile of demand is quite similar to the gross one, and it shows peaks at the same hours of the day. The generic profile is then split into many time bands. The length of each time band differs one from the other because the NGD in any band can be represented by an elementary function, and its value is independent from the values of the previous and next bands. For each time band, it is possible to identify a main point in such a manner that its value defines the NGD values of all the other (dependent) points of the same band.

The selection of the main points and the length of the intervals, of which each main point is the most relevant value, comes from the observation of data and from the perceptible existence of patterns of NGD that could be represented by simple equations with small error for short intervals. The shape of the patterns is strongly related to users' behaviours, which, in turn, are a complex function of climate, habits, rules and the cost of energy. The best way to find the main point of each interval is to look for the point that shows the strongest cross-correlation with the external temperature. The procedure can be easily implemented in Excel or MATLAB, even though the selection of the proper extension of the intervals requires manual trial and error.

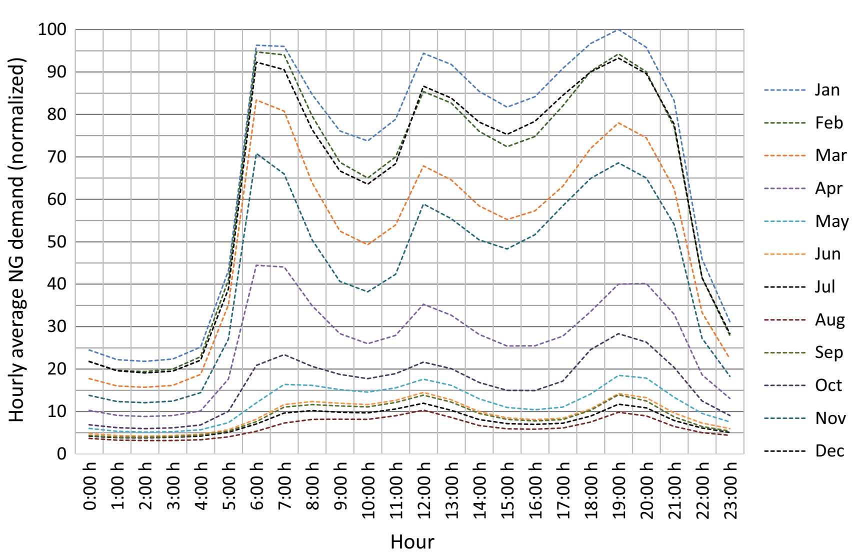

Fig. 3. Hourly average NGD (normalized).

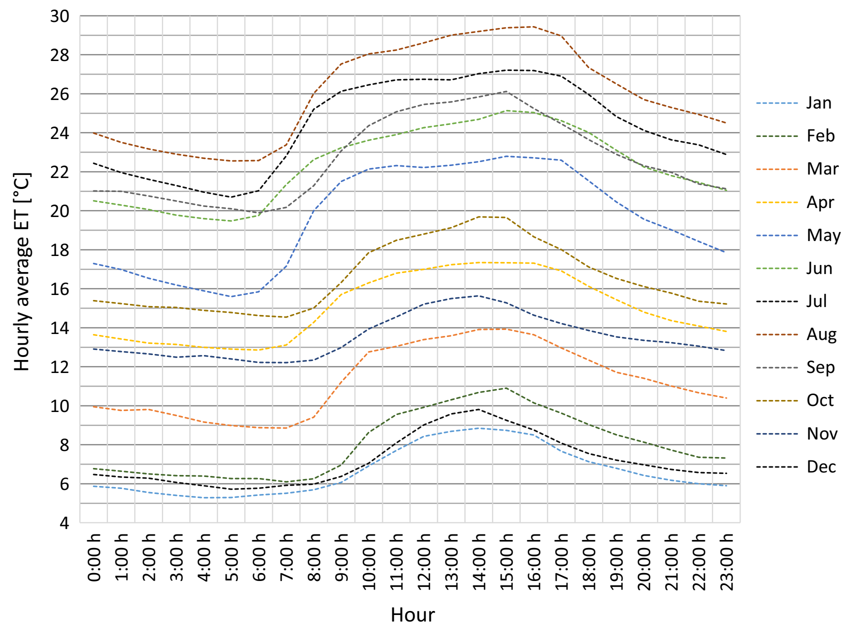

Fig. 4. Hourly average ET [°C].

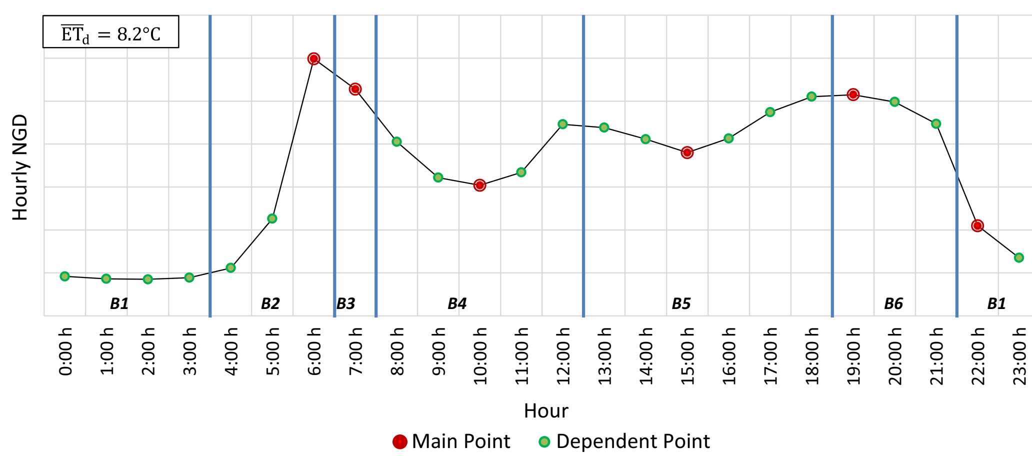

Fig. 5. Example of the NGD daily trend cleaned by HSAD.

For each main point, a linear correlation between the NGD value and the daily average $\overline{ET}_d$ was found. As an example, the red line in Fig. 6, represented by Eq. (1), shows the correlation between the main point NGD_{11} and $\overline{ET}_d$:

$$NGD_h = p_1\overline{ET}_d + p_2 \qquad [\mathrm{Sm^3/h}] \tag{1}$$

where NGD_h are the forecasted hourly NGDs and $\overline{ET}_d$ is the average daily ET. The coefficients p_1 and p_2 for the linear regression are confidential data from the NG distribution company, and Table 1 reports the coefficients, normalized by the average hourly NGD, of the SHOn period.

The profile of demand, in each time band, consists of a specific family of elementary functions; Table 2 summarizes, for each time band, its range, the main point and the regression function, where c_h are the regression coefficients (listed in Table 3).

The mean accuracy of the NGD forecasting model is within 20%. Error is higher at the extremes of the range of interest, i.e., for $\overline{ET}_d$ values lower than 3 °C or higher than 17 °C.

At present, the model does not distinguish the weekdays from the weekend, and it does not take into account the different habits and behaviours of the citizens during festivities. A more detailed prediction could be achieved using two different models for weekdays and the weekend or, alternatively, a curve for each day of the week.

6. Model for forecasting single-user hourly heat demand

The second step of this study consisted of the development of a simple and reliable forecasting model of the thermal and NG demand for a single building or a single flat from the perspective of using it as the component that describes end-users' behaviour for employment in the dynamic modelling of an entire DHN.

For this purpose, it has been assumed that a good approximation of the hourly heat demand of a single flat resembles the hourly profile of the mass flow rate of NG at the town level and that the first one can be obtained from the latter by means of a proper scaling factor K (Eq. (2)).

$$D_{build,h} = K \cdot NGD_h \qquad [\mathrm{kWh/h}] \tag{2}$$

where $D_{build,h}$ is the energy demand of a specific building and K is a specific coefficient for each building. Because energy demand resembles NG demand, it is assumed that the scaling factor between

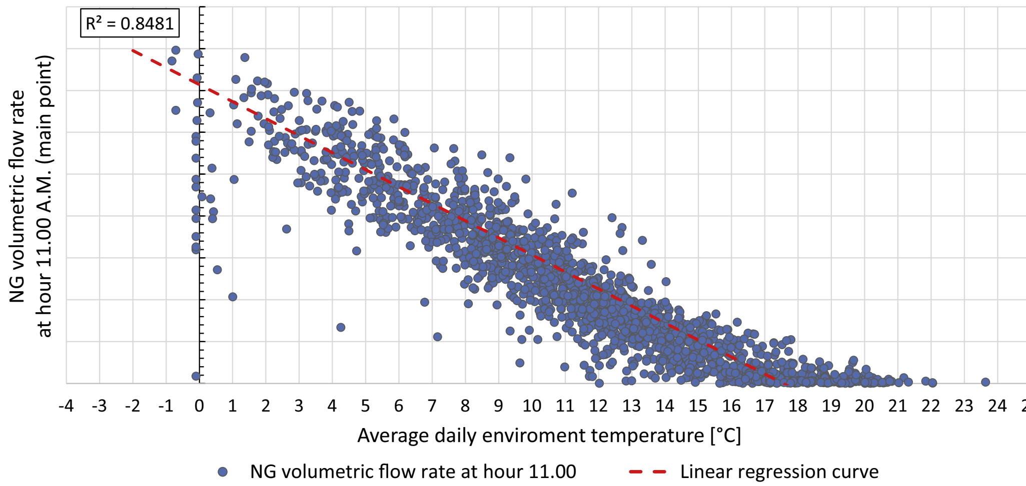

Fig. 6. Linear regression between ET and NGD at 11.00 o'clock.

Table 1
Coefficients for the linear correlation of the main points.

Main point	$\hat{p}_1$ [$Sm^3/h\,°C$]	$\hat{p}_2$ [Sm^3/h]
07	−8.319	187.7
11	−7.813	135.2
16	−9.098	164.0
20	−9.945	192.8
23	−4.395	83.41

Table 2
Functions for the correlation between NGD of the main points and the dependent points.

Time band	Range	Main point	Function
1	23–04	23	$NGD_h = NGD_{23} \cdot c_h$
2	05–07	07	$NGD_h = NGD_7 \cdot \exp(0.9366(h-7))$
3	08	08	$NGD_h = (NGD_7 + NGD_9)/2$
4	09–13	11	$NGD_h = NGD_{11} \cdot (1 + 0.1139 \cdot (h-11)^2)$
5	14–19	16	$NGD_h = NGD_{16} \cdot c_h$
6	20–22	20	$NGD_h = NGD_{20} \cdot c_h$

Table 3
Regression coefficients.

Time band	Coefficients	
1	C_1	0.4978
	C_2	0.4473
	C_3	0.441
	C_4	0.4522
	C_{23}	1
	C_{24}	0.6372
5	C_{14}	1.075
	C_{15}	1.028
	C_{16}	1
	C_{17}	1.056
	C_{18}	1.172
	C_{19}	1.257
6	C_{20}	1
	C_{21}	0.9626
	C_{22}	0.8469

the hourly and the annual NG demand is equal to that between the hourly and annual thermal demand:

$$K = \frac{D_{build,year}}{NGD_{year}} \frac{HDD_{real}}{HDD_{law}} \quad \left[\frac{kW}{Sm^3/h}\right] \tag{3}$$

the specific reduction coefficient K is defined for this purpose (Eq. (3)). The subscript year indicates the amount of energy per year.

The annual energy consumption required for heating of a generic building is obtained according to the Italian legislation regarding energy certification of residential buildings.

The legislation indicates the value of annual energy demand (kWh/m^2 year), or the Energy Performance Indicator Limit (EP_{Li}) [51], for a "D" energy class building. The norm defines the expected annual thermal demand of a building using the geometric characteristics, the energy classification and climatic data as the HDD value.

The main geometrical parameter that affects the thermal demand of buildings is the aspect ratio between the area of the external surface and the internal volume, S/V. In fact, heat losses to the environment are proportional to the area of the external surface, and it is clear that, for a fixed living space, the lower the S/V value is, the lower the energy requirements are.

As previously stated, the duration of the heating period at a specific location in Italy depends on the reference value of HDD, which assigns the location to a climatic zone. The city of Genoa, with an average of 1435 HDD (HDD_{law}), is in the "D" zone [49].

To calculate the real value of K, the conventional value of the annual heat demand is needed. This can be calculated, according to the Italian normative, for a flat in the "D" climatic zone, interpolating the data reported in Table 4 in the following way (Eq. (4)):

$$\begin{aligned} X_{S/V,HDD} = {} & X_{0.2,1400} + \\ & + \frac{S/V - 0.2}{0.9 - 0.2}(X_{0.9,1400} - X_{0.2,1400}) + \\ & + \frac{HDD - 1400}{2100 - 1400}(X_{0.2,2100} - X_{0.2,1400}) + \\ & + \frac{S/V - 0.2}{0.9 - 0.2} \cdot \frac{HDD - 1400}{2100 - 1400} \cdot \\ & \cdot (X_{0.9,2100} - X_{0.2,2100} - X_{0.9,1400} + X_{0.2,1400}) \\ & [kWh/m^2 year] \end{aligned} \tag{4}$$

Table 4
Building EP_{Li} for the D climatic zone.

EP_{Li} [$kWh/year\,m^2$]		
	HDD [°C day]	
	1401	2100
$S/V \leqslant 0.2$ [1/m]	21.3	34
$S/V \geqslant 0.9$ [1/m]	68	88

Table 5
Correction factors of EP_{Li} for different energy classes.

	$A^+ <$	$0.23 * EP_{Li}$
$0.23 * EP_{Li}$	$\leqslant A <$	$0.45 * EP_{Li}$
$0.45 * EP_{Li}$	$\leqslant B <$	$0.65 * EP_{Li}$
$0.65 * EP_{Li}$	$\leqslant C <$	$0.85 * EP_{Li}$
$0.85 * EP_{Li}$	$\leqslant D <$	$1.00 * EP_{Li}$
$1.00 * EP_{Li}$	$\leqslant E <$	$1.50 * EP_{Li}$
$1.50 * EP_{Li}$	$\leqslant F <$	$2.00 * EP_{Li}$
$2.00 * EP_{Li}$	$\leqslant G$	

The energy demand of a building characterized by a higher or lower energy class can then be easily calculated using the correction factors given in Table 5.

Hence, from the corrected EP_{Li} value, $D_{build,h}$ can be easily calculated by multiplying it by the building's floor surface.

Finally, the forecasting model for NG demand of the city estimates the total annual energy demand, NGD_{year}, and the correct value of degree-days, HHD_{real}.

The entire procedure has been developed using MATLAB Simulink [52]. From the user's point of view, the code is represented by a block (Fig. 7) whose input is the average daily $\overline{ET}_d$ and whose output is $D_{build,h}$.

A specific mask is used to set all the parameters of the building that are needed for calculation.

7. Applications of the model

This section describes some possible applications of the model to show how it can be used for real-world purposes. The first one consists of the comparison of the heat demand of buildings from three different energy classes and under various climatic conditions with fixed geometric parameters.

In particular, the simulations are performed for five days that are representative of the SHOn period and that have a daily average temperature equal to the monthly average ET values (Table 6) measured during the heating period.

Fig. 8 shows the daily heat demand for a specific building using the mean temperature of each month in the SHOn period. It can be observed that the mean hourly heat demand at night-time in December, January and February is more than three times higher than that in April and November, while the 7-o'clock peak in December, January and February is less than twice the corresponding peak in April and November. The hourly heat demand of a typical apartment in Genoa was calculated for a daily average temperature of 7 °C. Reference values for buildings in Genoa were assumed as follows: the Surface/Volume ratio, S/V, was equal to $0.25\ m^2/m^3$, and the mean extension was $82\ m^2$; these data are taken from documents of the Ligurian Regional Energy Agency [53] and are mainly based on Genoa's Sustainable Energy Action Plan [54].

Then, Fig. 9 shows the hourly heat demands calculated for three apartments that have equal internal floor area and volume but belong to three different energy efficiency classes, namely "A," "D" and "G". It is easy to appreciate the striking difference of consumption between an energy-effective building and a low-efficiency one. According to the Italian legislation, a "D" class apartment, with S/V = 0.25 and $82\ m^2$, would have an annual demand, $D_{build,year}$, of 1972 kWh/year. From Table 5, it is possible to see that the "A" class apartment would have an energy demand that is approximately 45% of the "D" class one, while for the "G" class, it would be twice as high.

To conclude, the model predicts the details of the dynamic of the thermal load that the flat would generate with a DHN if it were connected to it or, for instance, the magnitude of the oscillation of heat loads during the daytime.

A detailed project of complex and integrated heating systems cannot rely only on the estimation of the maximum thermal loads. The correct sizing of the components and the proper design of the mutual interaction among them stems from a detailed analysis of

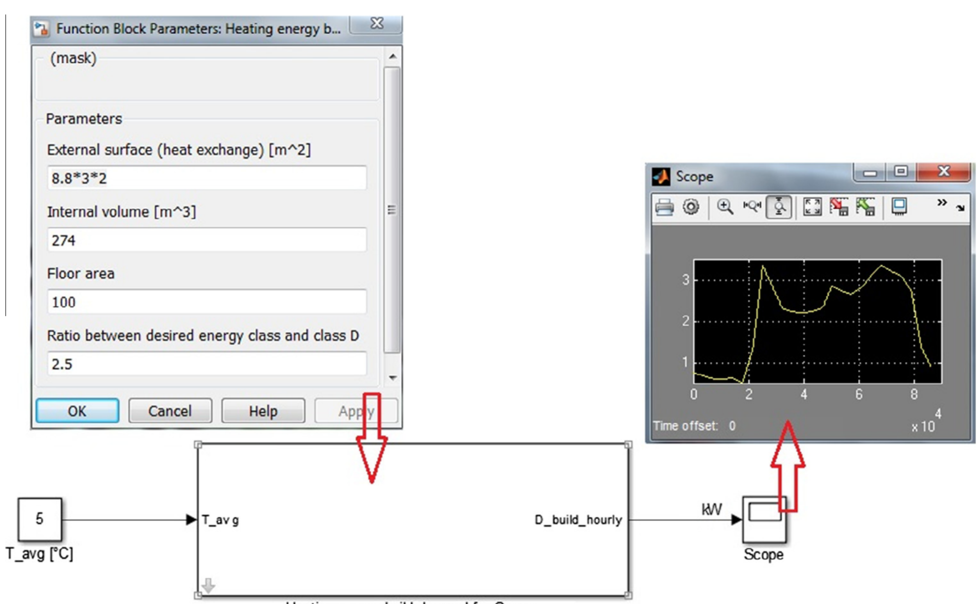

Fig. 7. MATLAB Simulink building heating demand forecaster block.

Table 6
SHOn period monthly average ET (2004–2011).

	Nov	Dec	Jan	Feb	Mar	Apr
ET_{avg} [°C]	13.5	7.2	6.6	8.0	11.2	15.0

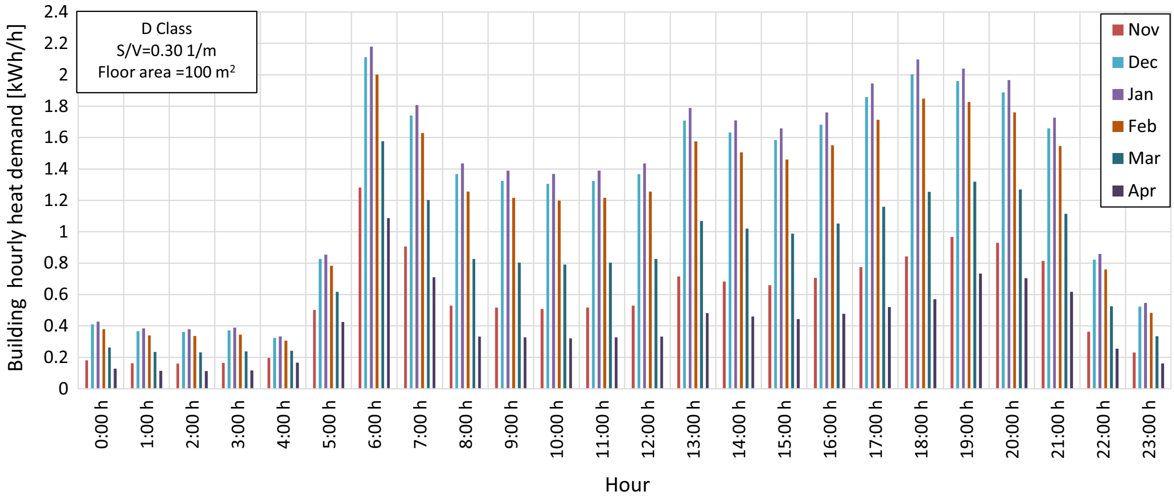

Fig. 8. Daily heat demand for a specific building during the SHOn period.

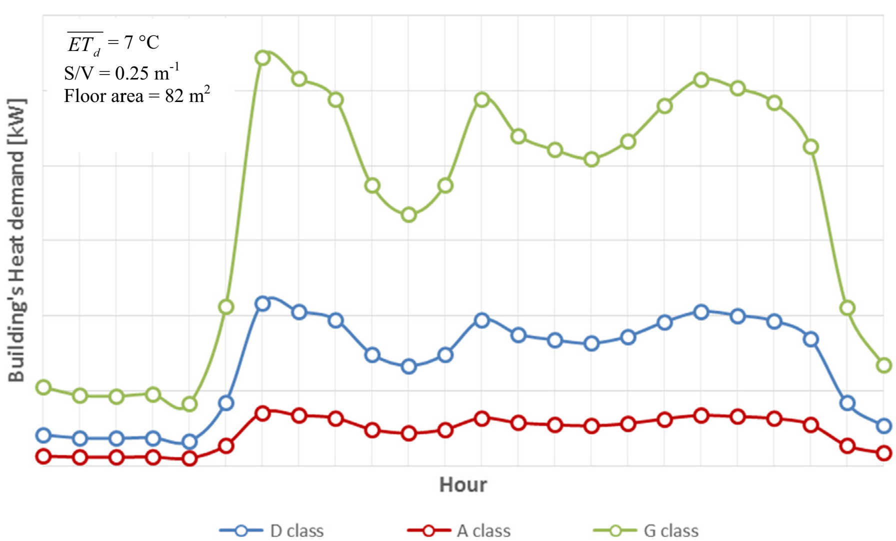

Fig. 9. Heat demand comparison for apartments with different energy classes (7 °C average daily ET).

load profiles, which can be simply accomplished by means of the proposed methodology. Fig. 10 shows the hourly heat demand for a large school building, calculated in the climatic design conditions of the city of Genoa. The red dots represent the daily heat demand peaks in the most adverse climatic conditions. Therefore, they express the maximum thermal power required by the building.

Unlike conventional boilers, whose size can be defined just by the maximum thermal demand, the sizing of components of integrated heating systems, such as the cogenerators, auxiliary boilers and heat storages used for DHNs and large plants, must be accomplished considering the heat demand profiles and the interactions between the components themselves. Also in this condition, the model is helpful for calculating specific features of the hourly heat demand, as shown in Figs. 11 and 12. Fig. 11 reports the profile of the hourly heat demand of a large old building with poor insulation (Class G) under the design condition of a daily average ET of 0 °C. The model predicts that the peaks of hourly heat demand are approximately 60% higher than the average and that they are concentrated into two definite periods of the day. This prevision could be profitably used to manage these peaks. Fig. 12 shows the difference between the peak and the daily average of hourly heat demand for three apartments that each have an internal floor area of 78 m^2 and that belong to energetic classes A, D and G, respectively, calculated with ET equal to 7 °C, which represents an average condition for December.

In recent years, there has been increasing attention on research on thermal storage because this is a key issue for better exploitation of renewable sources and their integration into a complex system of demands and sources. The proposed modelling can then be used to facilitate this development. The patterns of hourly heat demand are essential to the integration of daily energy storage within the infrastructure to improve its flexibility and efficiency. In particular, the profiles of the demand are necessary to match, through energy storage, the heat generated by cogenerators, as well as to select the most convenient source for each period of the day.

Lastly, the proposed model is particularly suitable for urban energy planning because it allows the analysis of large areas or large numbers of users, as needed for SEAP or Energy Atlases. When it is requested to evaluate the energy demand at the district or city level, the municipalities and the public administrations can

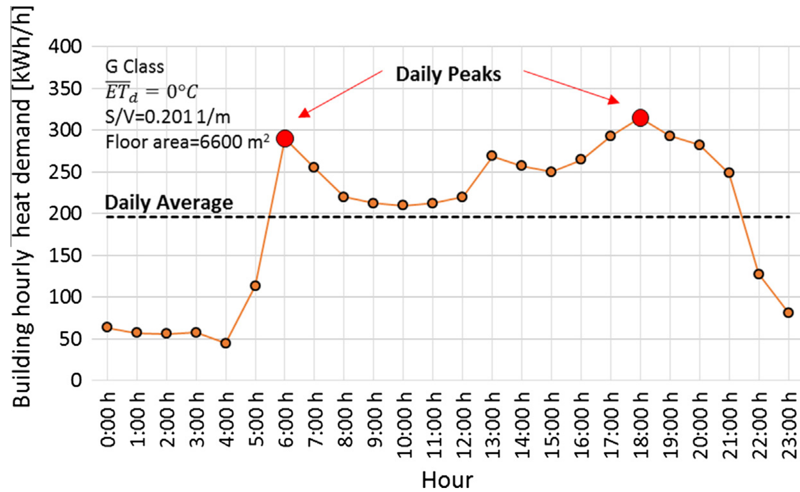

Fig. 10. Hourly heat demand for a "G-class" public building under the design condition (0 °C daily average ET).

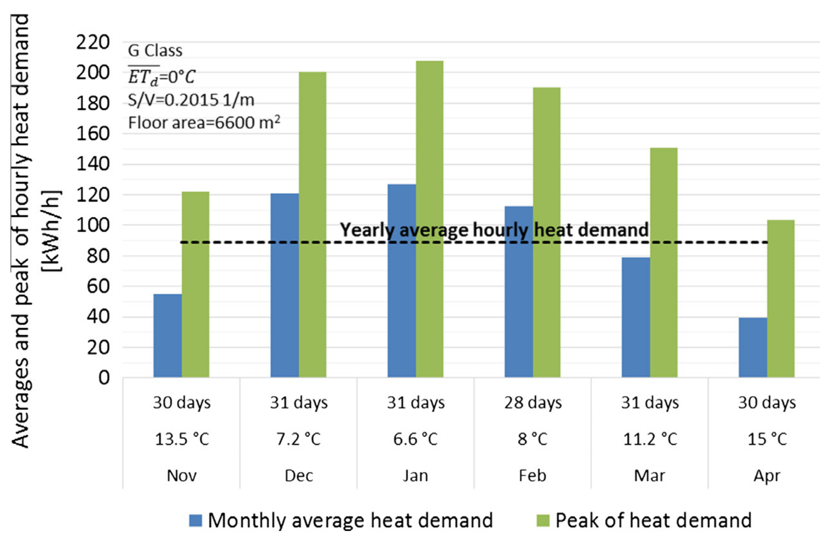

Fig. 11. Monthly average heat demand for a "G-class" public building.

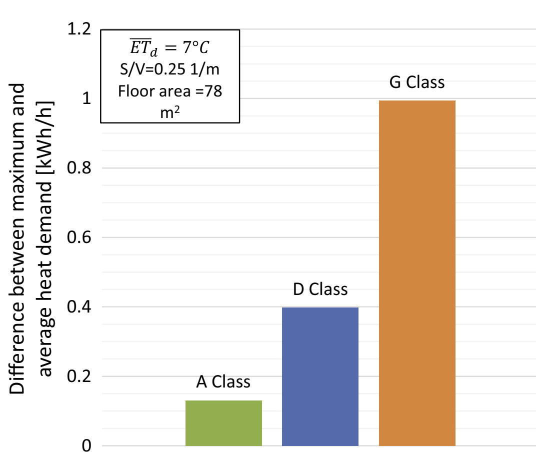

Fig. 12. Difference between the peak and the daily average heat demand for three apartments (A, D and G energetic classes).

find here a useful approach for facing the increasing necessity of a quick assessment of heat consumption to drive the general energy policy at an urban or regional scale.

8. Conclusions

In this study, a simple model for forecasting the hourly heat demand of a building has been developed. For this purpose, Genoa's hourly natural gas demand over a decade was analysed. The hourly profile of the average natural gas demand can be split into six time bands a day, and the consumptions, at any hour of each band, can be related to the value at a certain hour (main point) of the band itself. Furthermore, a simple correlation was found between the natural gas demand at the main points and the average daily temperature.

In the second part, the paper describes a procedure aimed at scaling down natural gas consumption measurements, which are often available only at a town level of aggregation, to predict single users' hourly heat demand. The main result of this procedure is that this model is able to describe the hourly profile of heat consumption of a flat on the basis of the daily average temperature. In this manner, if this model were used in conjunction with data obtained from daily weather forecasts, which currently predict the average temperature of the next day with a high level of accuracy, it would predict, one day in advance, the hourly profile of single users' heat demand.

The procedure demonstrated in this work infers the details of final users' hourly heat demand, starting from aggregate data of consumption, and implicitly describes the general habits of citizens. For this reason, this model is particularly useful for representing the dynamic thermal demand of single or groups of end-users in wide dynamic models of DHNs. This is of particular interest in cases in which researchers have access to aggregate data but the details of end-user consumption are not available.

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References

[1] Energy Information Administration (EIA). Annual energy outlook, 2013.
[2] The Italian regulatory authority for electricity and gas (AEEG). Annual report to the agency for the cooperation of energy regulators and to the European commission on regulatory activities and the fulfillment of duties of the Italian regulatory authority for electricity and gas. Annual report 2012. Autorità per l'energia elettrica e il gas; 31 July 2012.
[3] Soldo B. Forecasting natural gas consumption. Appl Energy 2012;92:26–37. http://dx.doi.org/10.1016/j.apenergy.2011.11.003.
[4] Sabo K, Scitovski R, Vazler I, Zekić-Sušac M. Mathematical models of natural gas consumption. Energy Convers Manage 2011;52:1721–7. http://dx.doi.org/10.1016/j.enconman.2010.10.037.
[5] Bianco V, Scarpa F, Tagliafico LA. Scenario analysis of nonresidential natural gas consumption in Italy. Appl Energy 2014;113:392–403. http://dx.doi.org/10.1016/j.apenergy.2013.07.054.
[6] Göncü A, Karahan MO, Kuzubaş TU. Forecasting daily residential natural gas consumption: a dynamic temperature modelling approach. Boğaziçi University Institute of Social Sciences working paper series, paper EC 2013–11. Retrieved on 28/2/2015 at: http://www.econ.boun.edu.tr/content/wp/EC2013_11.pdf.
[7] Swan Lukas G, Ugursal V Ismet. Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. Renew Sustain Energy Rev 2009;13(8):1819–35. http://dx.doi.org/10.1016/j.rser.2008.09.033.
[8] Suganthi L, Samuel AA. Energy models for demand forecasting—a review. Renew Sustain Energy Rev 2012;16(2):1223–40. http://dx.doi.org/10.1016/j.rser.2011.08.014.
[9] Kramer Rick, van Schijndel Jos, Schellen Henk. Simplified thermal and hygric building models: a literature review. Front Archit Res 2012;1(4):318–25. http://dx.doi.org/10.1016/j.foar.2012.09.001.
[10] Neto Alberto Hernandez, Fiorelli Flávio Augusto Sanzovo. Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. Energy Build 2008;40(12):2169–76. http://dx.doi.org/10.1016/j.enbuild.2008.06.013.
[11] Li Kangji, Su Hongye. Forecasting building energy consumption with hybrid genetic algorithm-hierarchical adaptive network-based fuzzy inference system. Energy Build 2010;42(11):2070–6. http://dx.doi.org/10.1016/j.enbuild.2010.06.016.
[12] Li Kangji, Su Hongye, Chu Jian. Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy system: a comparative study. Energy Build 2011;43(10):2893–9. http://dx.doi.org/10.1016/j.enbuild.2011.07.010.
[13] Yang Jin, Rivard Hugues, Zmeureanu Radu. On-line building energy prediction using adaptive artificial neural networks. Energy Build 2005;37(12):1250–9. http://dx.doi.org/10.1016/j.enbuild.2005.02.005.
[14] Ekici Betul Bektas, Aksoy Betul Bektas Teoman. Prediction of building energy consumption by using artificial neural networks. Adv Eng Softw 2009;40(5):356–62. http://dx.doi.org/10.1016/j.advengsoft.2008.05.003.
[15] González Pedro A, Zamarreño Jesús M. Prediction of hourly energy consumption in buildings based on a feedback artificial neural network. Energy Build 2005;37(6):595–601. http://dx.doi.org/10.1016/j.enbuild.2004.09.006.
[16] Strzalka, Bogdahn J, Coors V, Eicker U. 3D City modeling for urban scale heating energy demand forecasting. HVAC&R Res 2011;17(4):526–39. http://dx.doi.org/10.1080/10789669.2011.582920.
[17] Yu Zhun, Haghighat Fariborz, Fung Benjamin CM, Yoshino Hiroshi. A decision tree method for building energy demand modelling. Energy Build 2010;42(10):1637–46. http://dx.doi.org/10.1016/j.enbuild.2010.04.006.
[18] CEN Umbrella Normative prEn 15603. Energy performance of buildings—overall energy use, CO_2 emissions and definition of energy ratings; 2008.
[19] Tronchin Lamberto, Fabbri Kristian. Energy performance building evaluation in Mediterranean countries: comparison between software simulations and operating rating simulation. Energy Build 2008;40(7):1176–87. http://dx.doi.org/10.1016/j.enbuild.2007.10.012.
[20] Široký Jan, Oldewurtel Frauke, Cigler Jiří, Prívara Samuel. Experimental analysis of model predictive control for an energy efficient building heating system. Appl Energy 2011;88(9):3079–87. http://dx.doi.org/10.1016/j.apenergy.2011.03.009.
[21] Oldewurtel Frauke, Parisio Alessandra, Jones Colin N, Gyalistras Dimitrios, Gwerder Markus, Stauch Vanessa, et al. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy Build 2012;45(February):15–27. http://dx.doi.org/10.1016/j.enbuild.2011.09.022.
[22] Nannei E, Schenone C. Thermal transients in buildings: development and validation of a numerical model. Energy Build 1999;29(3):209–15. http://dx.doi.org/10.1016/S0378-7788(98)00060-7.
[23] Jain RK, Smith KM, Culligan PJ, Taylor JE. Forecasting energy consumption of multi-family residential buildings using support vector regression: investigating the impact of temporal and spatial monitoring granularity on performance accuracy. Appl Energy 2014;123(15):168–78. http://dx.doi.org/10.1016/j.apenergy.2014.02.057.
[24] Liu N, Tang Q, Zhang J, Fan W, Liu J. A hybrid forecasting model with parameter optimization for short-term load forecasting of micro-grids. Appl Energy 2014;129(15):336–45. http://dx.doi.org/10.1016/j.apenergy.2014.05.023.
[25] Richardson I, Thomson M, Infield D. A high-resolution domestic building occupancy model for energy demand simulations. Energy Build 2008;40(8):1560–6. http://dx.doi.org/10.1016/j.enbuild.2008.02.006.
[26] Widén J, Lundh M, Vassileva I, Dahlquist E, Ellegård K, Wäckelgård E. Constructing load profiles for household electricity and hot water from time-use data—modelling approach and validation. Energy Build 2009;41(7):753–68. http://dx.doi.org/10.1016/j.enbuild.2009.02.013.
[27] Fan C, Xiao F, Wang S. Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. Appl Energy 2014;127(15):1–10. http://dx.doi.org/10.1016/j.apenergy.2014.04.016.
[28] Olofsson T, Mahlia TMI. Modeling and simulation of the energy use in an occupied residential building in cold climate. Appl Energy 2012;91(1):432–8. http://dx.doi.org/10.1016/j.apenergy.2011.10.002.
[29] EN 832. European standard. Thermal performance of buildings-calculation of energy use for heating-residential buildings. Brussels (Belgium): European Committee for standardization; 1998.
[30] Pisello L, Goretti M, Cotana F. A method for assessing buildings' energy efficiency by dynamic simulation and experimental activity. Appl Energy 2012;97(September):419–29. http://dx.doi.org/10.1016/j.apenergy.2011.12.094.
[31] Braun MR, Altan H, Beck SBM. Using regression analysis to predict the future energy consumption of a supermarket in the UK. Appl Energy 2014;130(1):305–13. http://dx.doi.org/10.1016/j.apenergy.2014.05.062.
[32] Lee Y-S, Tong L-I. Forecasting nonlinear time series of energy consumption using a hybrid dynamic model. Appl Energy 2012;94(June):251–6. http://dx.doi.org/10.1016/j.apenergy.2012.01.063.
[33] Yao R, Steemers K. A method of formulating energy load profile for domestic buildings in the UK. Energy Build 2005;37(6):663–71. http://dx.doi.org/10.1016/j.enbuild.2004.09.007.
[34] Sailor David J, Muñoz J Ricardo. Sensitivity of electricity and natural gas consumption to climate in the USA—methodology and results for eight states. Energy 1997;22(10):987–98. http://dx.doi.org/10.1016/S0360-5442(97)00034-0.
[35] Sailor David J, Rosen Jesse N, Muñoz J Ricardo. Natural gas consumption and climate: a comprehensive set of predictive state-level models for the United States. Energy 1998;23(2):91–103. http://dx.doi.org/10.1016/S0360-5442(97)00073-X.
[36] Vondráček Jiří, Pelikán Emil, Konár Ondřej, Čermáková Jana, Eben Kryštof, Malý Marek, et al. A statistical model for the estimation of natural gas consumption. Appl Energy 2008;85(5):362–70. http://dx.doi.org/10.1016/j.apenergy.2007.07.004.
[37] Brabec Marek, Konár Ondřej, Pelikán Emil, Malý Marek. A nonlinear mixed effects model for the prediction of natural gas consumption by individual customers. Int J Forecast 2008;24(4):659–78. http://dx.doi.org/10.1016/j.ijforecast.2008.08.005.
[38] Aras Haydar, Aras Nil. Forecasting residential natural gas demand. Energy Sources 2004;26(5):463–72. http://dx.doi.org/10.1080/00908310490429740.
[39] Taşpınar Fatih, Çelebi Numan, Tutkun Nedim. Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods. Energy Build 2013;56(January):23–31. http://dx.doi.org/10.1016/j.enbuild.2012.10.023.
[40] Demirel ÖF, Zaim S, Çalişkan A, Özuyar P. Forecasting natural gas consumption in Istanbul using neural networks and multivariate time series methods. Turk J Electr Eng Comput Sci 2012;20(5):695–711. http://dx.doi.org/10.3906/elk-1101-1029.
[41] Askari S, Montazerin N, Zarandi MH Fazel. Forecasting semi-dynamic response of natural gas networks to nodal gas consumptions using genetic fuzzy systems. Energy 2015;83(1):252–66. http://dx.doi.org/10.1016/j. energy.2015.02.020.
[42] Forouzanfar Mehdi, Doustmohammadi Ali, Menhaj M Bagher, Hasanzadeh Samira. Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran. Appl Energy 2010;87(1):268–74. http://dx.doi.org/10.1016/j.apenergy.2009.07.008.

[43] Potočnik P, Soldo B, Šimunović G, Šarić T, Jeromen A, Govekar E. Comparison of static and adaptive models for short-term residential natural gas forecasting in Croatia. Appl Energy 2014;129(15):94–103. http://dx.doi.org/10.1016/j.apenergy.2014.04.102.
[44] Brown RH, Clark D, Corliss G, Nourzad F, Quinn T, Twetten C. Forecasting natural gas demand: the role of physical and economic factors. In: 32nd Annual international symposium on forecasting Boston, June.
[45] Soldo B, Potočnik P, Šimunović G, Šarić T, Govekar E. Improving the residential natural gas consumption forecasting models by using solar radiation. Energy Build 2014;69:498–506. http://dx.doi.org/10.1016/j.enbuild.2013.11.032.
[46] Fantini L, Schenone C. Degree-days, population distribution and heating energy consumption: the Italian case. Int J Ambient Energy 2001;22:199–210. http://dx.doi.org/10.1080/01430750.2001.9674859.
[47] http://www.covenantofmayors.eu/actions/sustainable-energy-action-plans_en.html [retrieved on 14/07/2016].
[48] http://celsiuscity.eu/ [retrieved on 14/07/2016].
[49] Decree of the President of the Italian Republic; 1993 [no 412].
[50] Decree of the President of the Italian Republic; 2013 [no 74].
[51] Bollettino Ufficiale della Regione Liguria; 2012 [no 20]. Retrieved on 10/03/2015 at: http://www.bur.liguriainrete.it/archiviofile/B_000000169912201000.pdf.
[52] MATLAB R2015a. Natick (MA): The MathWorks Inc.; 2015.
[53] Ligurian Regional Energy Agency. Spreadsheet for the analysis of primary energy consumption of park of the residential buildings of the Liguria region 2014.
[54] Sustainable Energy Action Plan (summary) of Genoa Retrieved on 10/03/2015 at:Available from: http://www.urbancenter.comune.genova.it/sites/default/files/archivio/allegati/SEAP%20summary_0.pdf2011.