Thermal load prediction in district heating systems

Elisa Guelpa[a], Ludovica Marincioni[b], Martina Capone[c], Stefania Deputato[d] and Vittorio Verda[d]

[a] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, elisa.guelpa@polito.it*
[b] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, ludovica.marincioni@polito.it*
[c] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, martina.capone@polito.it*
[d] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, stefania.deputato@polito.it* [d]
[e] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, vittorio.verda@polito.it*

Abstract

Optimal operation of district heating (DH) systems usually relies on the forecast of thermal demand profiles of the connected buildings. Depending on the purpose of the analysis, thermal request can be required at various levels, from building level to thermal plant level. In the case of demand response for example, thermal request is necessary at a building level to evaluate its applicability and at a plant level to determine the effects. Thermal request profiles are quite different, depending on the observation point. Total requests are not just the summation of the downstream requests, mainly because of the thermal transients. The heat losses also contributes to modify the curves, although generally in a smaller way.
In this work, a multi-level thermal request prediction is proposed. This approach has the aim of evaluating the thermal request in the various sections of DH network with reduced computational resources. This includes a compact model for the prediction of building demand and a network model in order to compose together the requests at the various levels. The application to a portion of the Turin district heating network is proposed. This shows that the network dynamics significantly affects the evolution, especially at peak load.

Keywords: load forecast, demand prediction, multi-level approach, thermal network model, thermal fluid dynamic, district heating network

1. Introduction

District heating (DH) is an increasingly widespread technology for house heating and domestic hot water production, especially in highly populated areas [1]. In some European countries as Denmark, this is used to provide more than 60 % of the heat demand to buildings [2]. DH is an important technology for improving energy efficiency in urban areas. In fact, it enables shifting heat generation from domestic boilers to a) high efficiency plants [3,4] b) industrial waste heat [5, 6] c) renewable energy sources [7, 8]. This represents a strength from two points of view: from an end-user perspective, because the energy cost is generally lower and because the issues related to the domestic boiler maintenance and control are avoided; from a community and environmental point of view, because it avoids environmental emissions thanks to the lower primary energy consumption and the decarbonisation of the energy source.
Management of DH networks is a crucial point to achieve high efficiency. A smart selection of the operating plants allows a significant primary energy saving (especially when RES and waste heat are available). Additional primary energy savings can be obtained through an optimal selection of working conditions of pumps [10]. Optimal management of networks in case of malfunctions (leakages or pump failure) can lead to a drastic improvement of the comfort conditions in buildings[11]. Proper use of storage can lead to a

significant decrease of primary energy consumption [12]. Optimal network management also allows solving possible hydraulic bottlenecks and connect as much buildings as possible to a network without modifying the network pipelines [13].

Intelligent management of DH systems relies on detailed knowledge of the thermal request at various levels: building level, distribution network level or thermal plant level. Some examples are:

- Thermal demand at building level for operating actions such as demand side management [14-16].
- Request at a distribution network or a group of distribution networks for storage installation (optimal design, position) and management [17], as well as for defining optimal pumping strategies.
- Thermal load at a plant level for taking decisions on optimal plant operation.

The thermal load profile at the plants might be very different than the demand at the buildings, because of the thermal transients, the losses towards the environment and the mixing effects of the various streams coming from the various areas of the network. Depending on the application, it is important to consider the thermal request at proper level.

The thermal request profile within the day at a building level, can be predicted through advanced tools for building analysis (such as Energy Plus) or black box models (neural networks, machine learning etc). The first approach [18, 19] uses physical principles to calculate thermal dynamics and energy behavior of buildings. Models based on this approach are expected to provide precise results because they simulate the physics of the phenomenon. On the other hand, they require high computational resources and precise input data in order to obtain results with a sufficient level of accuracy. This makes them unsuitable when a large number of buildings is considered.

In contrast, black box approaches provide results with low computational costs but results are less detailed [20, 21]. These models are suitable for applications to large systems and when dealing with measurements available in thermal substations. Various works in the literature propose models for predicting the overall request of DH relying on historical data [22-25].

A schematic including the models currently used for building demand evaluation is reported in Fig. 1 [26]. The figure shows that, when the demand of single buildings is evaluated, small time frames are considered, while in case of higher number of buildings the time frame is generally high, especially when the analysis is made for planning purpose. In case of DH management, the thermal demand of buildings is necessary with low time frame, of the order of few minutes.

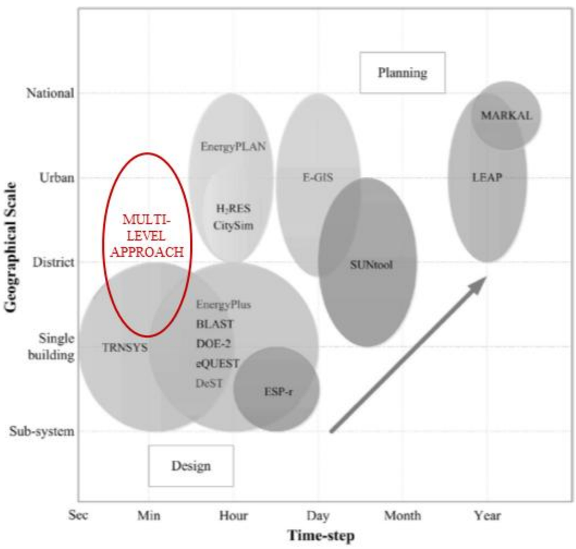

Fig. 1 Model for thermal request prediction in DHN [26], including the approach here proposed

The present paper proposes a multi-level method to predict the request of buildings in DH systems. It is based on a) a compact model for the prediction of building demand profiles in DH b) a network model for the evaluation of the thermal request at various levels (distribution network, group of distribution networks, plant level). The goal of the method here proposed is to predict the thermal request at different levels of the network only relying on a) the historical data in the buildings substation b) the network topology. Prediction of the thermal demand at building level can be obtained by means of a black box model relying on the data

that are usually available in building connected to DH (e.g. measurements from smart meters used for billing purposes). This allows one evaluating the request of all buildings connected to a network with low computational costs. A physical model of the DH network is then combined with the building demand prediction to properly aggregate the request at various levels (at a subnetwork level, at a thermal plant level, etc.,) taking the transient effects as well as the heat losses and flow mixing processes into account.
The contribution of this work consists in providing an approach for the evaluation of the thermal request in each section of a DH network, starting from information which is reasonably available and considering the important effects of network dynamics. This approach can be applied to DH optimization both at a management level and a design level. In a multi-energy framework, this can be used for all the applications where knowledge of the request in a certain time/point is required. Among them are the evaluation of opportunities and constraints for the use of heat pumps [27-29], thermal energy storage units [30-32], plant operations or to apply a demand response management. These are discussed in section 5.

2. Methodology

2.1 Multi-level approach

The thermal request at the plants may be very different than the summation of the thermal demands of the buildings. This difference is due to various factors: the network dynamics, the heat losses and the different behaviour of the buildings in the various zones of the network. In this paper, a multi-level approach is proposed to predict the thermal request at various network levels (depicted in Fig. 2). The methodology here presented consists in the following steps:

- A smart predictor (black box approach) of the thermal demand evolution of the buildings. This is a compact model relying only on data that are usually available for the thermal substations in modern networks (such as the inlet and outlet temperatures and the mass flow rate on the primary side).
- A network physical model able to combine the demand of the various buildings and to account for the fluid flow and heat transfer in the network.

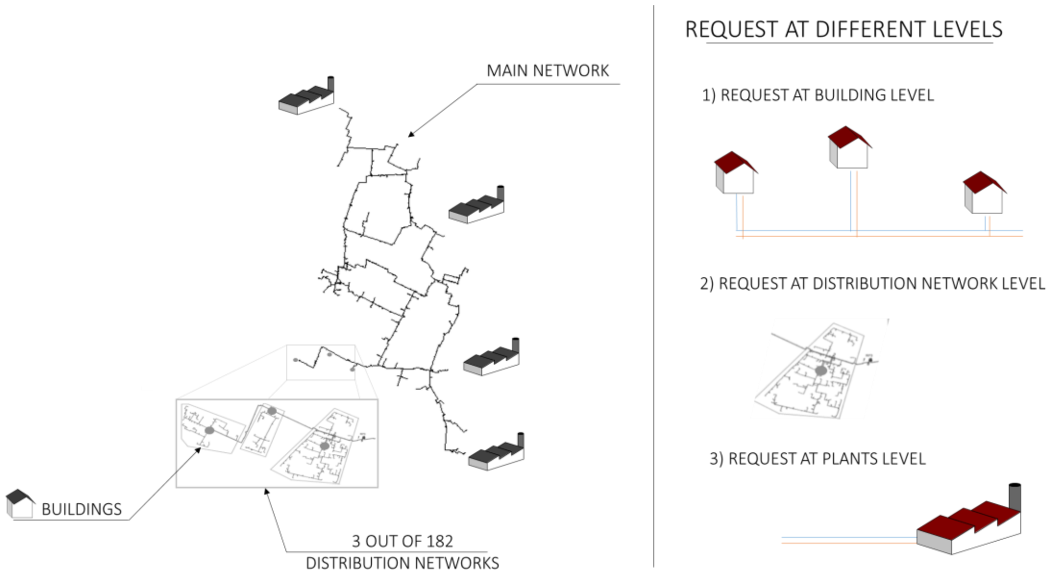

Fig. 2. Schematic of the different level requests

The two models are described in section 2.2 (Building demand prediction) and 2.3 (Network physical model). A schematic of the complete methodology here proposed is reported in Fig. 3. The building demand prediction is performed by means of a black box model, which is based on historical data collected during the previous months or seasons. In particular, substation data and meteorological data are collected. Substation data are gathered using a system installed in each substation, i.e. the one used to evaluate the thermal request for billing purposes. These are temperature and mass flow rates at the substation heat exchanger. Data are deeply described in section 3. The collected data need to be pre-processed, by eliminating data gaps, and their structure is reorganized. Meteorological data consist of maximum, minimum and average temperature daily values. Meteoreological data can be obtained from temperature sensors in the substations or purchased from third parties. Substation and meteorological data are used to calibrate the black box model. Once the black box model is built, if meteorological conditions of a certain day are known, this provides the thermal request at a building level.

Once the thermal request at building level is evaluated, it is possible to obtain the thermal request at a distribution network level by relying on the physical model, given the distribution network topology (characteristics of pipes and their interconnections). This is done by using the results of the prediction model as boundary conditions of the physical network model as explained in section 2.3.

In the end, it is possible, relying on the network topology of the transport network (the main network), evaluating the thermal request in the various points of the main network, such as for a group of distribution networks or at plant level. This is done by using the thermal request at distribution level as boundary conditions of the physical network model.

Information and tools that should be available in order to implement the methodology are reported in green in Fig. 3. These are:

- A system for the collection of the data in the substation (that allows collecting T_{hist} and G_{hist}), usually available for billing purposes.
- A tool for properly manage the collected data to delete data gaps.
- The environmental conditions of the days when T_{hist} and G_{hist} are gathered.
- The topology of the DH network.

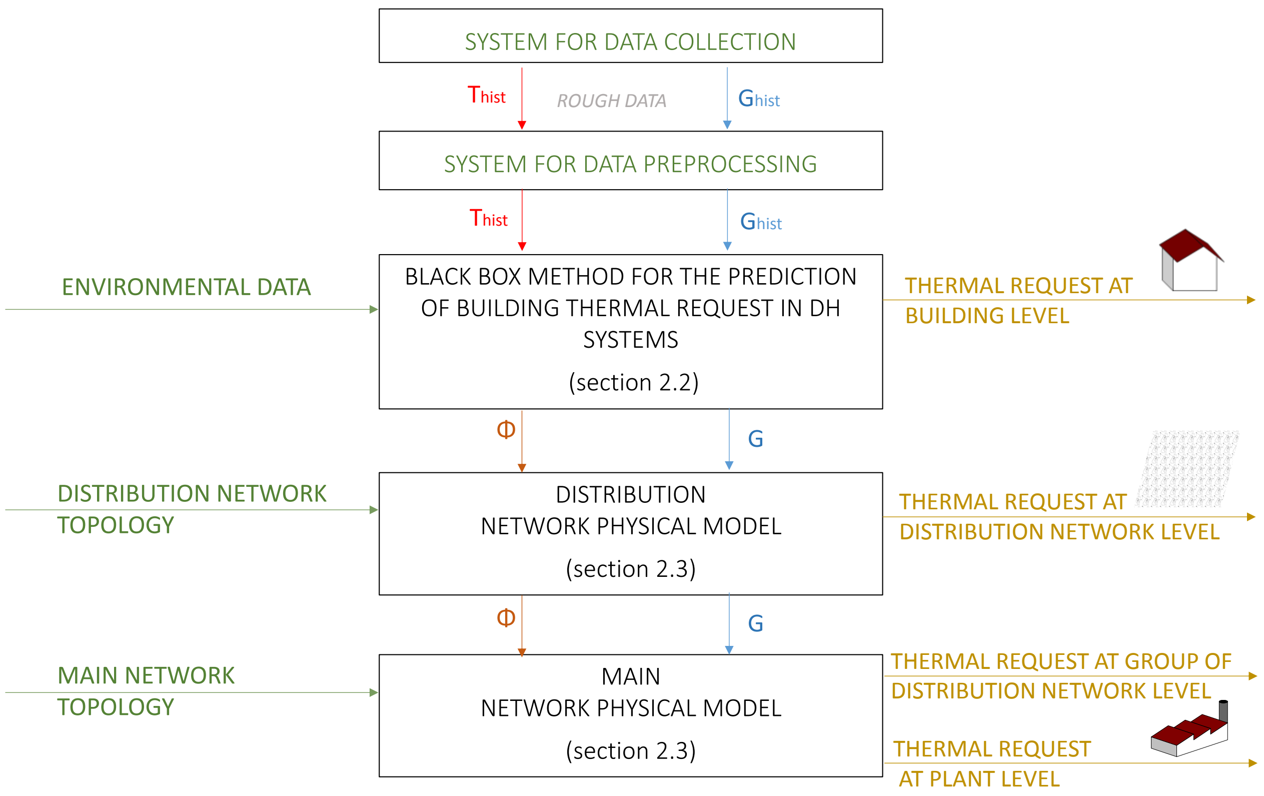

Fig. 3. Methodology description

2.2 Buildings demand prediction

Building demand prediction is mainly based on the idea to simplify the thermal profile, so that it can be identified using a small number of variables. Using this approach, prediction of these variables is sufficient to construct the demand profile, instead of predicting the complete evolution. This allows reducing the effects of two types of errors: those due to model complexity and those due to data gathering and transmission. In fact, complex models require a large amount of data to be calibrated and are particularly sensitive to measurement errors; in addition, when dealing with collection of data from a large number of substations, missing data or wrong measurements to be filtered off might appear. When compact models are used, these issues can be easily detected and tackled. Fig. 4 shows the main characteristics of the adopted approach. The various parts are described in the following subsections.

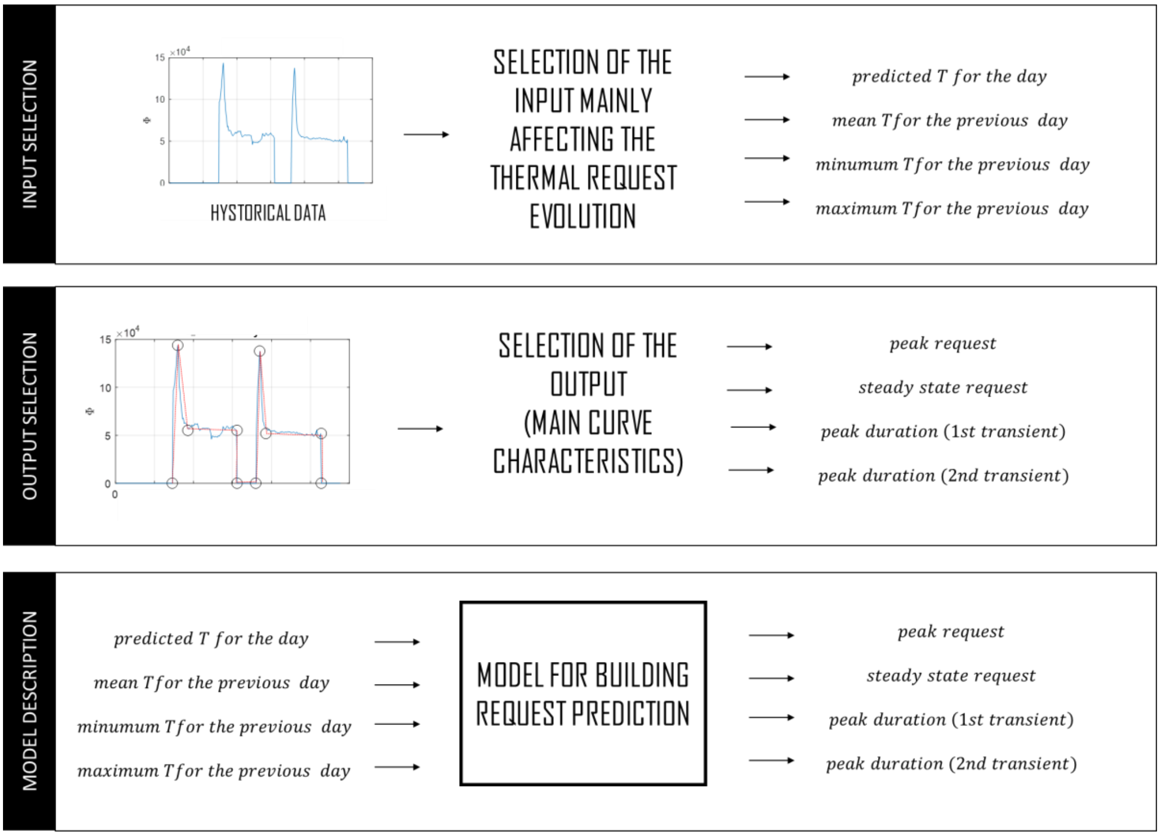

Fig. 4. Structure of the prediction model for building demand profiles

2.2.1 Black box model

A linear model has been used for the evaluation of the main points which describe the thermal demand evolution of buildings. The schematic of the model used is presented in Fig. 2 (last box). The form of the linear model can be described by equation 1, in a matrix form.

$$Y = \gamma_0 + \gamma_1 X \tag{1}$$

where:

- the vector Y (n x 1) includes the output of the model, described in section 2.2.2, which are the main characteristics of the curve;
- the vector X (m x 1) includes the input of the model, described in section 2.2.3, which are the set of independent variables;
- γ0 and γ1 are respectively the constant term vector (n x 1) and the coefficient matrix (n x m).

The model is calibrated by using substation and meteorological data collected in the previous seasons, that are used to evaluate γ0 and γ1. The same modelling approach is adopted to evaluate the mass flow rate request at each building.

2.2.2 Selection of the output of the prediction model

Looking at the building request evolution shown in Fig. 5, it is clear that the main features are: a peak demand occurring when the heating system is switched on and a steady state following the peak. The time when peaks occur and the duration of the steady state depend on the heating schedule, i.e. when the system is switched on and off. The following quantities can be thus evaluated for each building:

- the maximum elevation of the peak;
- the steady-state heat demand;
- the time which is needed for reaching the maximum point of the peak after the heating system is switched on;
- the time which is needed for reaching the end point of the peak after the maximum;

The schedules for the heating systems are set on the substations upon request of the end-users, therefore these are known values which do not need an estimation. All these quantities are reported in Fig. 5.

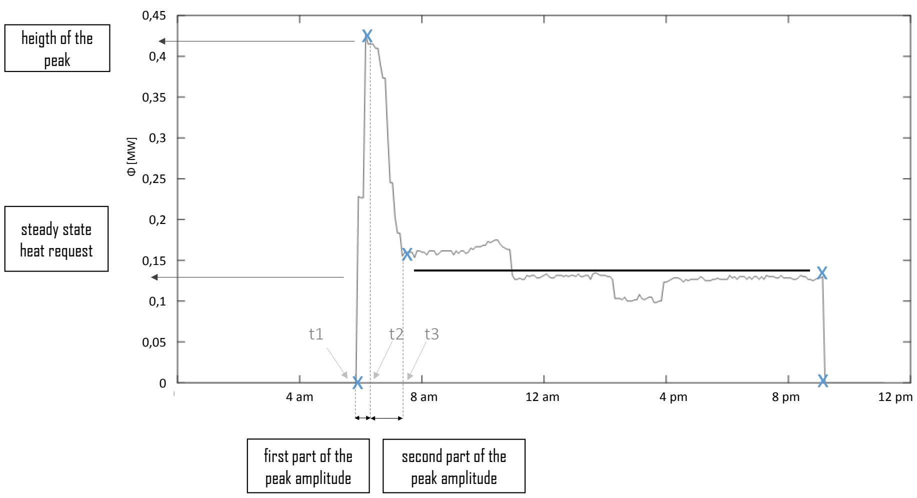

Fig. 5 Key points in the demand profiles

Detection of these quantities should be made automatic, because it is necessary to produce a sufficiently large historical dataset for a large number of buildings. For this reason, the following procedure has been implemented using a proper software (in this case a Matlab function has been created):

- first of all, abnormal values are eliminated by excluding the peaks which values are too large when compared with the corresponding steady states (e.g. more than 4-10 times, depending on the average external temperature) and the values which do not fit at all correlations with the external temperatures;
- the maximum elevation of the peak is evaluated as the highest value of each day;

$$\Phi_{\max} = \max(\Phi) \tag{2}$$

- the steady-state heat demand is evaluated as the average of all the thermal load values comprised between the end point of the peak and the following switching off time.

$$\Phi_{steady} = \frac{1}{N}\sum_{t=t3}^{t4}\Phi \tag{3}$$

  where N is the number of samples between t_3 (end peak time) and t_4 (switching off time).

- the time the system requires for reaching the maximum point of the peak from the switching on time is evaluated as the difference between the time the two events occur.

$$w1 = t2 - t1 \tag{4}$$

  t_1 is the switching on time and t_2 the maximum peak time.

- the time the system requires for reaching the end point of the peak from the maximum is evaluated as the difference between the time the two events occur.

$$w2 = t3 - t2 \tag{5}$$

  where t_3 is the end-peak time

The evaluation of the final point of the peak requires particular care. Each points after the maximum peak is gathered and it is considered as the end of the peak if one of the two following options is satisfied:

- the slope of the curve has an absolute value which is lower than a threshold;
- the heat flux is smaller than the steady state.

When a heating system which is switched on more than once a day is considered, the same approach is used as many times as the number of operation periods. Therefore, the daily evolution is divided into various periods (when the system is switched on i.e. the thermal power is different than zero) and for each period the same analysis is repeated.

2.2.3 Selection of the input of the prediction model

In order to identify the most appropriate input of the model, various parameters have been considered:

- the average temperature of the previous day, $T_{m,d-1}$;
- the minimum temperature of the previous day, $T_{min,d-1}$;
- the maximum temperature of the previous day, $T_{max,d-1}$;
- the average temperature of the current day, $T_{m,d}$;
- the solar radiation, I;
- the air humidity, ϕ;
- the wind velocity, v;

In order to evaluate which of these quantities mostly influence the main characteristics of the thermal demand evolution, a correlation analysis has been performed by using the Pearson index. The Person index of two variables is defined as the covariance over the product of their standard deviations. Results of the correlation analysis show that the quantities that mostly affect the thermal request evolutions are the four temperatures. The air humidity and wind velocity have a negligible effect on the demand profile. The latter is justified by the fact that Turin is located in a geographic area characterized by low wind velocities. Solar radiation mainly affects the evolution of indoor temperatures, while its main effect on the demand profiles is somehow captured by the difference between minimum and maximum temperatures. For these reasons only the four temperatures are considered as the input for the model. It is worth to mention that a forecast for the average temperature in the current day is needed to use the model.

2.3 Network model for changing the request level

A network model is used in order to analyse the water dynamics within the pipelines. The model is based on a graph approach, which is used to provide a mathematical representation of the network structure [33]. Following a 1D approach, each pipe of the network is considered as a branch that starts from a node, (the inlet node) and ends in another node (the outlet node). The incidence matrix, A, describes the network topology by expressing the connections between nodes and branches. This matrix has as many rows as the number of nodes and as many columns as the number of branches. The general element A_{ij} is equal to 1 or -1 if the branch j enters or exits the node i and 0 otherwise. The thermal fluid-dynamic model considers:

- the mass conservation equation applied to all the nodes and the momentum conservation equation applied to all the branches. These equations are here considered in steady state, since fluid-dynamic perturbations travel the entire network in a period of time smaller than the time step adopted for calculations (60 s). The resolution of the fluid dynamic relies on an iterative approach because the problem is nonlinear since the two equation are coupled and the dependence of pressure from the mass flow is quadratic. Further details on the method are available in [34] and [35]. The solved equations are:

$$\mathbf{A} \cdot \mathbf{G} + \mathbf{G}_{\mathbf{ext}} = 0\,, \tag{6}$$

$$\boldsymbol{G} = \boldsymbol{Y} \cdot \boldsymbol{A}^{T} \cdot \boldsymbol{P} + \boldsymbol{Y} \cdot \Delta \boldsymbol{p}_{pumps}\,, \tag{7}$$

where **G** is the vector including the mass flow rates in branches, G_{ext} the vector includes the mass flow rates exiting the nodes towards the extern, **P** the vector including the pressures in the nodes and Δp_{pumps} is the pressure difference in the pumping stations. The diagonal matrix **Y** represents the fluid dynamic conductance of branches that can be written as:

$$Y = R^{-1} = \left[\frac{1}{2} \frac{G}{\rho S^2} \left(\frac{f}{D} L + \sum_k \beta_k \right) \right]^{-1} \quad (8)$$

- The thermal model is expressed in transient form since thermal perturbations travel the network at the water velocity, which is the order of few meters per second, depending on the request and the portion of network. Therefore temperature variations take a lot of time to reach the thermal plants.

The energy conservation equation for a node can be written as:

$$\rho\, c \frac{\partial T}{\partial t} + \rho\ \ c\, v \cdot \nabla T = \varphi \quad (9)$$

The first term is the transient term, the second one represents the advective contribution due to mass flow rates in all the branches connected to the node, the right-hand side term includes the contribution of thermal source and losses. Eq. 9 is obtained by considering negligible compressibility effects, viscous heating and heat conduction. Considering the problem as one dimensional, by integration, it is possible to obtain:

$$\frac{\partial (\rho c \Delta T)_i}{\partial t} \Delta V_i + \sum_j c G_j\, T_j = U\, (T_i - T_{gr}) \quad (10)$$

where the thermal losses are written as the product of the global heat exchange coefficient U and the temperature difference between the water in the pipe and the temperature of the ground around the pipe. This can be re-written in a matrix form, as follows:

$$\mathrm{M}\dot{\mathrm{T}} + \mathrm{KT} = \gamma \quad (4)$$

where **M** is the mass matrix, **K** is the stiffness matrix, **T** is the vector of nodal temperatures and **γ** the vector of known terms. Since the thermal model includes the unsteady term, it allows catching the transient phenomena, such as the delay of various cold and hot streams within the network, due to their distance and velocity.

As boundary conditions, temperature and mass flow rates of the inlet and outlet flows are required. For the distribution network simulation, mass flow rate imposed as boundary conditions are achieved by the approach in 2.2.1, while temperature of water exiting the substation are evaluated since thermal request, mass flow rate and inlet temperature are known (the last one by means of the network physical model applied to the supply line). Concerning the transportation network level, mass flow rates and temperature evaluated by the distribution network model are used as boundary conditions.

3. Case Study

The test case considered in this work is the Turin DH system. The buildings connected to the network are about 6500 (each building includes a heat exchanger). A schematic of the network is provided in Fig. 6. The main transport network, depicted in black, is characterized by larger diameters and links the thermal plants to the various distribution networks, which in the Turin system are 182. The distribution networks are characterized by smaller diameters and link the consumers located on the same areas to the transportation network. In Fig. 6, as an example, 3 of the 182 distribution network are depicted in the blue circles. Production and storage sites are also included in Fig. 6.The network is supplied with pressurised hot water at 120°C while return ranges between 50°C and 70°C. For further details on the analysed system refers to [32].

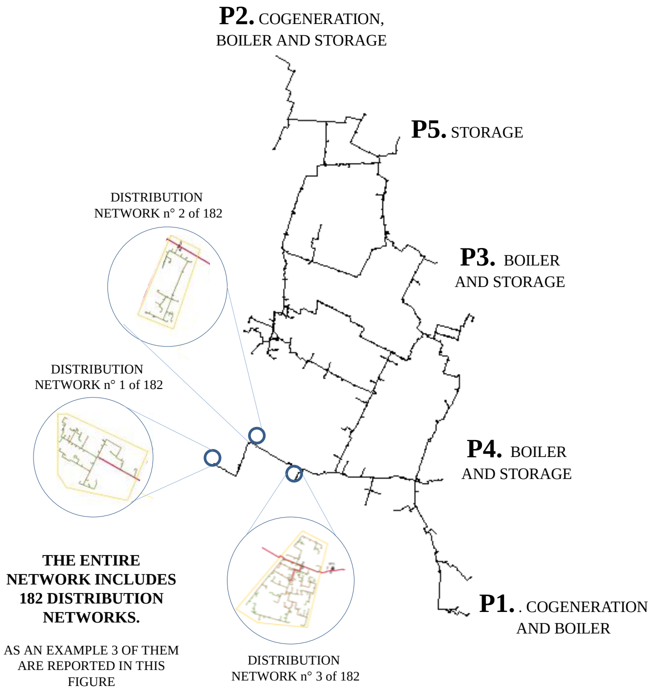

Fig. 6. Schematic of the DH analysed in the case study including transportation network and three of the distribution networks

The large number of buildings connected to the Turin network makes the use of automatic system for the evaluation of thermal profiles necessary. Forecast of the thermal profiles is done by means of data gathered at the substations. The measured quantities are:

- the mass flow rate at the primary side of the heat exchanger, G;
- the temperature at the inlet section of the primary side, T1;
- the temperature at the outlet section of the primary side, T2;
- the temperature at the inlet section of the secondary side, T4;
- the temperature at the outlet section of the secondary side, T3;
- the environmental temperature, T_{env}.

Fig. 7 shows the evolution of data gathered in a seven buildings of a distribution network of the Turin system; mass flow rates (G) and thermal power (ϕ) are shown. The latter quantity is calculated from the measurements of mass flow rate and the two temperatures on the primary side. Most of the heating systems are switched off during the night and switched on between 5 a.m. and 6 a.m. When a system is switched on, the mass flow rate and, consequently, the thermal profile present a peak, due to the low temperature of the fluid at the secondary side of the substation heat exchanger. The number of shutdowns of the systems is selected by the end-users and it is different in the various buildings (one, two or three times a day). This is a very important point for the thermal load prediction. In case of buildings that have no substation data available a different approach can be used, as shown in [36]

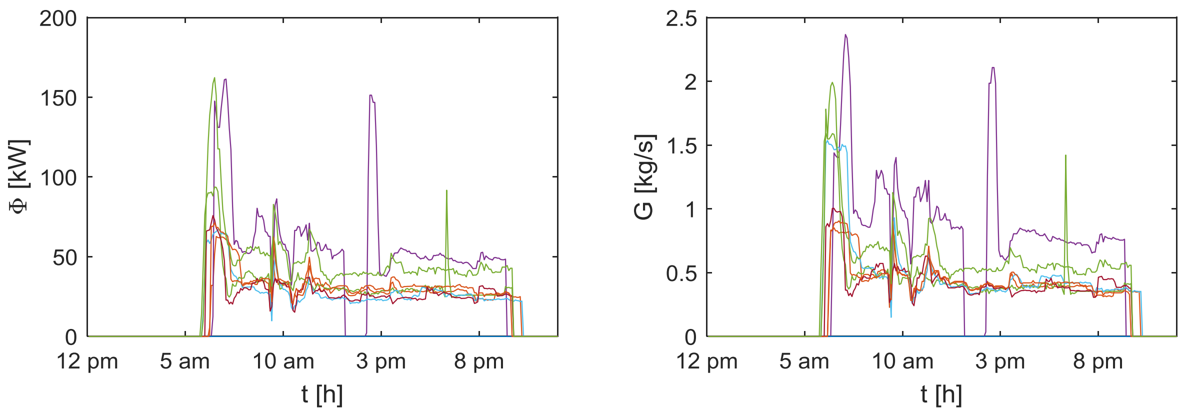

Fig. 7. Daily data gathered in the substations

Experimental data gathered during two entire seasons and the related meteorological conditions are used for calibrating the buildings thermal request model. This is done by 1) evaluating the main curve characteristics 2) estimating the coefficients γ_0 and γ_1 that allows characterizing the black box model. The model has been applied to various distribution networks, for an overall amount of three hundred buildings. Results obtained by the black box model and the network topology are used to evaluate the thermal request of a distribution network. The outcomes of this analysis are discussed in section 4.2. Thermal request of various distribution networks and the topology of the transport pipelines are used as input of the transport network model. This allows obtaining the thermal request in all the sections such as the request of a group of distribution networks, or the thermal load profile for a plant.

4. Results

Results presented in this paper are divided in three main parts. The first part (section 4.1) concerns the evaluation of the thermal request at building level (orange arrows in Fig. 8). The second part (section 4.2) deals with the thermal request at distribution network level (red arrow in Fig. 8). In the third part (section 4.3), results related to the thermal request at the thermal plants (dark red arrow in the Fig. 8) are shown and discussed.

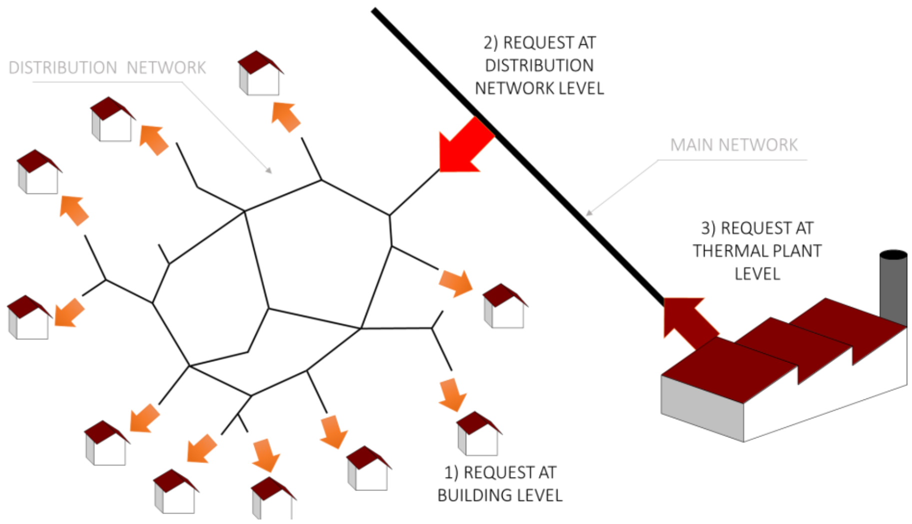

Fig. 8. Request at the various levels

4.1 Request at building level

Fig. 9a shows the results obtained through application of the automatic approach for detecting the main points of the demand profiles. The figure reports the experimental data measured in the substations (in blue) and the points detected using the automatic tool (in black). Eight substations have been analysed. These have been randomly selected with the aim of showing the potential of the system for the main point evaluation. In particular, the random selection is conceived such that buildings with one, two or three switching on per day are included. The points used to represent the curve are:

1. the switching on;
2. the peak;
3. the end-point of the peak;
4. the last time before the system is switched-off;
5. the time the system is switched off.

It is clear from Fig. 9a that the model for the automatic detection of the points perfectly detects all the quantities for all the considered cases.

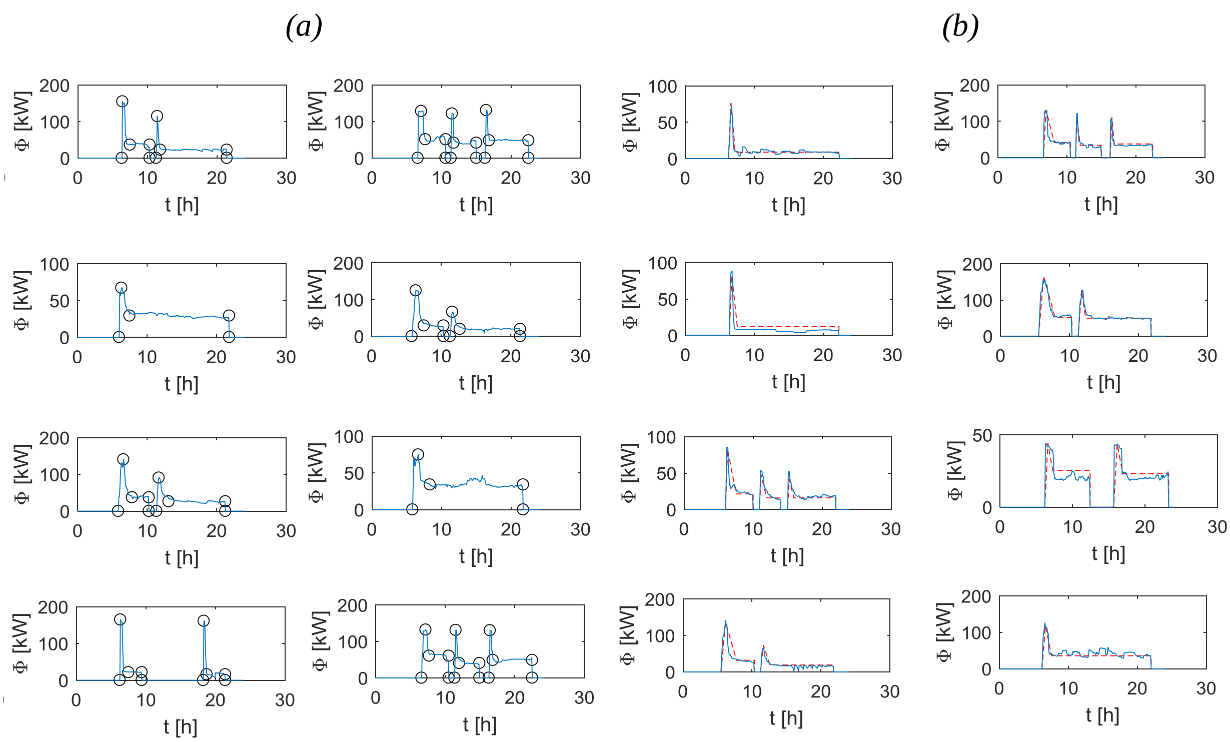

Fig. 9. Results of the model for the building demand forecast: a) tool for the automatic detection of the main curve characteristics b) comparison between real and predicted profiles

Fig. 9b shows a comparison of the thermal load forecast (dashed red line) and the real evolution (blue line). The thermal demand evolution is well detected in all the cases reported in the figure. The maximum peak values, the steady state condition, and the peak duration are predicted with an error lower than 10%The mean relative error that the model perform is evaluated as the mean error in the evaluation of the main curve characteristics. In particular, the percentage error on the maximum peak is less than 7 %. This is a satisfying result considering i) the very high variability of the thermal request ii) the problems related to the detection of data (one need only think the lack of a data at the maximum peak) iii) the imprecision due to wheatear forecast and iv) the use of a black box approach.

As regards the error performed on the prediction of the steady state, this is higher (although less than 15%)) than the ones performed predicting the maximum peak value. This is because especially at the beginning and at the end of the heating season, the steady state value are quite low and the relative error is quite low although the absolute value is small.

Another important point is the time that the model takes to provide results, during both the model building and the model use. The tool for the evaluation of the γ coefficients (including the pre-processing stages, such as the evaluation of the main curve characteristics) requires low computational times. In particular, in some seconds it allows one to obtain the optimal values of coefficients γ for a distribution network. As regards the model use, it only takes about 0.1 seconds. This result is very important because large networks includes various hundreds distribution networks and the model has to be run at least every month in order to include the changes in user request (mainly due to possible rescheduling of the operating hours in the buildings or the implementation of retrofitting measures).

4.2 Request at distribution network level

Fig. 10 shows the total demand at distribution network level, for a typical winter day. Both thermal request and mass flow rate are reported. The errors associated to the prediction of the distribution network request are, on average, lower than the errors at a building level. This is because, when various buildings are considered, the errors at the building level offset each other, because of their different signs. The water collected in the pipelines cooled down during the night switched on causes a large thermal peak due to the large temperature difference between supply and return.

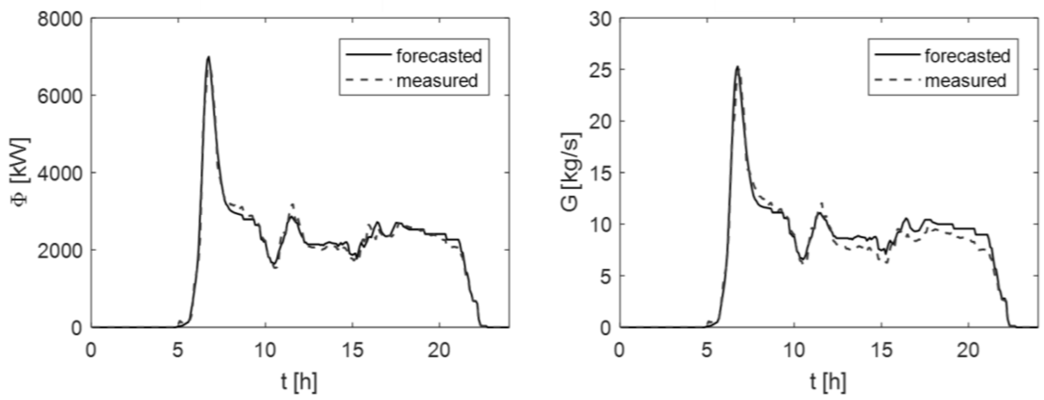

Fig. 10. Thermal request and mass flow profiles at distribution network level

The effects of the input variation on the error prediction are tested on a complete heating season. This allows taking into account the high variability of cases that can occur. Results are reported in Fig.11 where the relative error for the peak value and the steady state value predictions are shown. The relative error is computed as the difference between the value predicted and the value occurred (experimental data), divided by the maximum value occurred during the year. The errors are weighted respectively on the maximum peak value (in case of peak prediction) and the maximum steady state value (in case of steady state prediction). This allows avoiding mismatches between the error referred to days characterized by different outdoor conditions (characterized by different thermal request). A frequency plot is used to show how frequently a certain error occurs. The figure shows that the error are lower than 5 % in almost all the considered day.

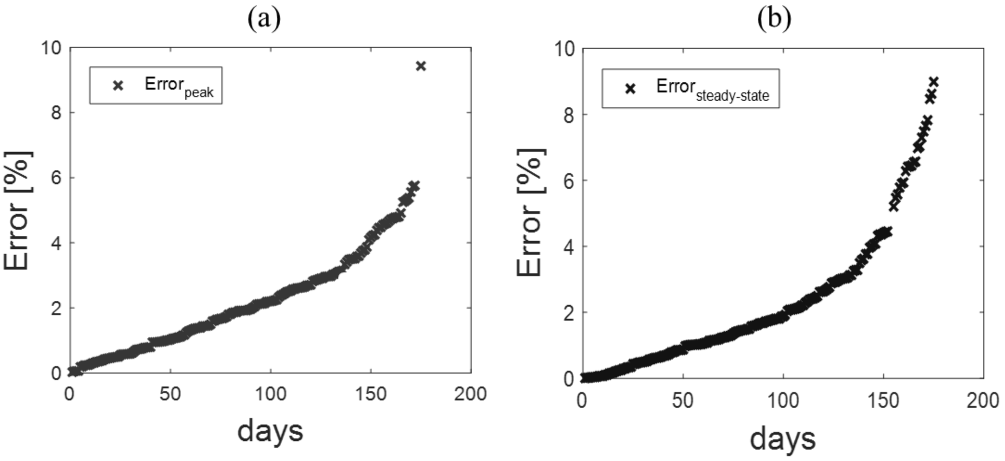

Fig. 11. Errors in the evaluation of the thermal request profile at distribution network level: a) error in the peak detection b) error in the steady state detection

4.3 Request at thermal plant level

In this section, the importance of using a multi-level approach is shown. Fig. 12 reports the thermal requests at various levels (depicted in Fig. 8):

- the summation of the thermal requests of the buildings connected to the network, called building level, since the dynamic of the network is not taken into account (yellow continuous line).
- the summation of the thermal requests of the various distribution networks, called distribution network level (orange dashed line). This includes the dynamics of the distribution networks but it does not include the dynamics of the transport network.
- the thermal load evolution, evaluated a thermal plant level (blue dashed-dot line). This includes the dynamics of both the distribution and the transport networks (plant level);

The thermal request is reported between 4 am and 8 am because at this time the thermal peak occurs and the effect of the mixing and the thermal transients. Fig. 12 clearly shows that the thermal request at plant level is significantly different from that at building level. The sum of thermal request at buildings is lower, mainly because it does not takes into account the temperature evolution during transients. At night, the mass of water flow rate in the pipeline is small and the percent thermal losses are high, with a consequent low temperature at night. In the morning, when the heating systems in the building are switched on, a large mass flow rate is processed at the plants and the temperatures in the return line are low. As a consequence, a large peak request occurs. The peak thermal request at distribution network level is higher than that at building level since distances are smaller and the buildings switch on heating systems at almost the same time. For this reasons the building peak request is significantly amplified. This clearly shows that the multi-level approach allows one taking into account the network dynamics when considering the request in various point (level) of the network.

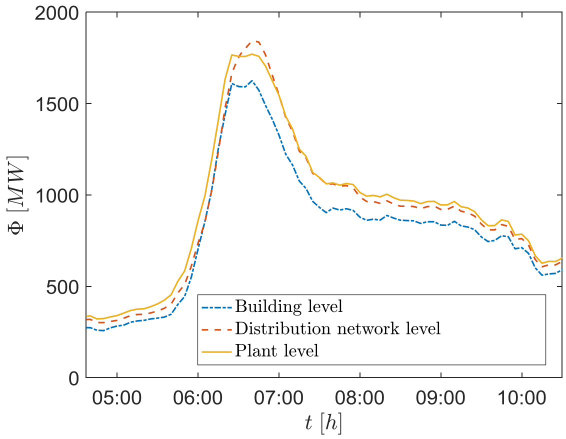

Fig. 12. Comparison of the thermal request at plant level evaluated at different levels

5. Discussion

A multi-level request predictor is crucial for analysing the management of large DH networks. This is due to the long distances involved, large amount of water and the slow transients. This might make the expected thermal request in a point very different from the actual request. Various analyses rely on the knowledge of the thermal request in various points:

- Demand side management in DH networks requires the knowledge of thermal request at building level. Demand side management is becoming more and more interesting for modifying the demand in order to follow the shape of the production evolution. This is going to be crucial in the future when renewable energy sources are going to supply large fraction of DH demand. Demand side requires knowledge of thermal request is because during:
    - It is necessary to select a certain number of buildings subjected to the modifications of the thermal request;
    - The modification should be properly selected depending on the evolution of the thermal request.
- Thermal requests at building level are required also for exploiting the capacity of buildings as a thermal storage.
- Thermal request in a part of the network should be known when the installation of a thermal storage or a new plant is planned. This is particularly true when the new system is installed with the main aim of overcoming hydraulic bottlenecks while feeding a specific part of the network. Installation of storage plants is crucial in future DH systems to guarantee maximum exploitation of high efficiency and renewable that can operate in a different time from that the time the request occurs.
- Installation of heat pumps for increasing the quality of a fluid should be performed once the thermal request evolution in a point of the network is known. This is very important in future frameworks of multi-energy systems, where different energy vector networks (thermal, electricity, gas, etc.) will be deeper interconnected.
- Management of thermal plants depends on the thermal request at plant level. It can be used with the aim of increasing the efficiency or to better exploit the resources from an economic viewpoint. In fact, in case of combined heat and electricity production, electricity production can be more convenient at some hours than others. Modification of the thermal load evolution at plant level may help increasing incomes deriving from electricity selling.

In case a change of the substation regulation strategy is planned the model should be adapted to be suitable for the new conditions. With this aim, a model for the simulation of the substation and building behaviour, like the one proposed in [16], can be used to predict the thermal request for buildings, by considering a different regulation strategy. Then, once the new regulation strategy is adopted, the data collected during the new regulation strategy usage can be used for calibrating the black box model.

6. Conclusions

In this paper, a multi-level approach to evaluate the thermal request in DH network is presented. The approach used for the predictor of the building request is based on the identification of a series of important curve characteristics for the thermal profile evaluation; these quantities are the peak height, the peak amplitude, the request during steady state conditions. In order to detect the main curve characteristics from historical data, an automatic tool has been carried out. The main inputs influencing the curve characteristics have been evaluated through a correlation analysis. The predictor model of the building thermal request is based on a black box approach. Historical thermal profiles and meteorological data are used for the model construction.

The change of level for the prediction (from building to distribution network and from distribution network to thermal plant) is performed by means of a physical network model. This allows taking into account mixing of water at different temperature, thermal losses and transient.

Results show that the tool for the automatic evaluation of the main curve characteristics perfectly detect the desired quantities. Results also show that the prediction model for both building and distribution network request allows detecting the profiles (error lower than 10%). The model is suitable for large DH networks, thanks to its compactness (the low number of input parameters and amount of data that have to be managed and the simplicity of application and implementation) ease of use and low computational costs.

Acknowledgments

Authors are very grateful to the technicians of IREN for providing the operation data used in this work

References

[1] Lund, H., Möller, B., Mathiesen, B. V., & Dyrelund, A. (2010). The role of district heating in future renewable energy systems. Energy, 35(3), 1381-1390.

[2]Euroheat and Power. District Heating and Cooling Country by Country Survey. 2013.

[3] Lindenberger, D., Bruckner, T., Groscurth, H. M., & Kümmel, R. (2000). Optimization of solar district heating systems: seasonal storage, heat pumps, and cogeneration. Energy, 25(7), 591-608.

[4] Casisi, M., Pinamonti, P., & Reini, M. (2009). Optimal lay-out and operation of combined heat & power (CHP) distributed generation systems. Energy, 34(12), 2175-2183.

[5] Sun, F., Fu, L., Sun, J., & Zhang, S. (2014). A new waste heat district heating system with combined heat and power (CHP) based on ejector heat exchangers and absorption heat pumps. Energy, 69, 516-524.

[6] Fang, H., Xia, J., & Jiang, Y. (2015). Key issues and solutions in a district heating system using low-grade industrial waste heat. Energy, 86, 589-602.

[7] Lund, H., & Mathiesen, B. V. (2009). Energy system analysis of 100% renewable energy systems—The case of Denmark in years 2030 and 2050. Energy, 34(5), 524-531.

[8] Lund, H. (2005). Large-scale integration of wind power into different energy systems. Energy, 30(13), 2402-2412.

[10] Sciacovelli, A., Guelpa, E., & Verda, V. (2013, November). Pumping cost minimization in an existing district heating network. In ASME 2013 International Mechanical Engineering Congress and Exposition (pp. V06AT07A066-V06AT07A066). American Society of Mechanical Engineers.

[11] Guelpa, E., & Verda, V. (2018). Model for optimal malfunction management in extended district heating networks. Applied energy, 230, 519-530.

[12] Zeghici, R. M., Damian, A., Frunzulică, R., & Iordache, F. (2014). Energy performance assessment of a complex district heating system which uses gas-driven combined heat and power, heat pumps and high temperature aquifer thermal energy storage. Energy and Buildings, 84, 142-151.

[13] Guelpa, E., Mutani, G., Todeschi, V., & Verda, V. (2018). Reduction of CO2 emissions in urban areas through optimal expansion of existing district heating networks. Journal of Cleaner Production, 204, 117-129.

[14] Guelpa, E., Deputato, S., & Verda, V. (2018). Thermal request optimization in district heating networks using a clustering approach. Applied Energy, 228, 608-617.

[15] Guelpa, E., Barbero, G., Sciacovelli, A., & Verda, V. (2017). Peak-shaving in district heating systems through optimal management of the thermal request of buildings. Energy, 137, 706-714.

[16] Verda, V., Guelpa, E., Sciacovelli A., F. G., Acquaviva, A., & Patti. (2016). Thermal peak load shaving through users request variations. International Journal of Thermodynamics, 19(3), 168-176.

[17] Söderman J. Optimisation of structure and operation of district cooling networksin urban regions. Appl Therm Eng 2007;27:2665–76

[18] Clarke, J. A. Energy simulation in building design. Routledge 2017

[19] Zhao, H. X., & Magoulès, F. (2012). A review on the prediction of building energy consumption. Renewable and Sustainable Energy Reviews, 16(6), 3586-3592.

[20] Ben-Nakhi, A. E., & Mahmoud, M. A. (2004). Cooling load prediction for buildings using general regression neural networks. Energy Conversion and Management, 45(13-14), 2127-2141.

[21] Braun, J. E., & Chaturvedi, N. (2002). An inverse gray-box model for transient building load prediction. HVAC&R Research, 8(1), 73-99.

[22] Potočnik, P., Strmčnik, E., & Govekar, E. (2015). Linear and neural network-based models for short-term heat load forecasting. Strojniški vestnik-Journal of Mechanical Engineering, 61(9), 543-550.

[23] Wojdyga, K. (2014). Predicting heat demand for a district heating systems. International Journal of Energy and Power Engineering, 3(5).

[24] Yang Hongying, Heat load forecasting of District Heating System based on Numerical Weather Prediction Model, 2nd International Forum on Electrical Engineering and Automation (IFEEA 2015), 2015 .

[25] Idowu, S., Saguna, S., Åhlund, C., & Schelén, O. (2016). Applied machine learning: Forecasting heat load in district heating system. Energy and Buildings, 133, 478-488.

[26] Ma, W., Fang, S., Liu, G., & Zhou, R. (2017). Modeling of district load forecasting for distributed energy system. Applied Energy, 204, 181-205.

[27] Li, Y., Fu, L., Zhang, S., & Zhao, X. (2011). A new type of district heating system based on distributed absorption heat pumps. Energy, 36(7), 4570-4576.

[28] Sciacovelli, A., Guelpa, E., & Verda, V. (2014). Multi-scale modeling of the environmental impact and energy performance of open-loop groundwater heat pumps in urban areas. Applied Thermal Engineering, 71(2), 780-789.

[29] Lindenberger, D., Bruckner, T., Groscurth, H. M., & Kümmel, R. (2000). Optimization of solar district heating systems: seasonal storage, heat pumps, and cogeneration. Energy, 25(7), 591-608.

[30] Bo, H., Gustafsson, E. M., & Setterwall, F. (1999). Tetradecane and hexadecane binary mixtures as phase change materials (PCMs) for cool storage in district cooling systems. Energy, 24(12), 1015-1028.

[31] Sibbitt, B., McClenahan, D., Djebbar, R., Thornton, J., Wong, B., Carriere, J., & Kokko, J. (2012). The performance of a high solar fraction seasonal storage district heating system–five years of operation. Energy Procedia, 30, 856-865.

[32] Sciacovelli, A., Guelpa, E., & Verda, V. (2014). Second law optimization of a PCM based latent heat thermal energy storage system with tree shaped fins. International Journal of Thermodynamics, 17(3), 145-154.

[33] Harary F. GraphTheory. Narosa Publishing House. New Delhi; 1995.

[34] Guelpa, E., Sciacovelli, A., & Verda, V. (2017). Thermo-fluid dynamic model of large district heating networks for the analysis of primary energy savings. Energy.

[35] Guelpa, E., & Verda, V. (2019). Compact physical model for simulation of thermal networks. Energy. In press.

[36] Guelpa, E., Marincioni, L., & Verda, V. (2019). Towards 4th generation district heating: Prediction of building thermal load for optimal management. Energy. In press.