Demand side management in district heating networks: a real application

Elisa Guelpa[a*], Ludovica Marincioni[a], Stefania Deputato[a], Martina Capone[a], Stefano Amelio[b], Enrico Pochettino[b], Vittorio Verda[a]

[a] *Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy*
[b] *IREN Spa, Corso Svizzera 95, 10129 Torino, Italy*

Abstract

Demand side management is one of the strategies for an optimal management of DH networks. This consists in rescheduling the time the heating systems are switched on and off, or modifying their settings. In this way, the thermal request profile results as changed, with the following effects: 1) additional buildings can be connected to the network without installing new pipelines; 2) a better exploitation of renewable energy sources can be achieved; 3) a reduction of the heat produced by heat-only boilers is obtained. This work shows the potential of demand side management in DH networks in terms of thermal peak shaving. This is done by optimally rescheduling building heating systems. The best rescheduling is evaluated by means of a simulation tool. An experimental test performed on a distribution network shows that a peak reduction of about 5% can be achieved in case of strong limitations on the modifications. Simulations show that a relaxation of limitations leads to a reduction up to about 35% of peak request.

Keywords: demand response, virtual storage, thermal network, district heating system management, optimization.

* *Corresponding author: PhD Elisa Guelpa, Energy department, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy, elisa.guelpa@polito.it, Tel: 0110904478*

1. Introduction

One of the keys for the success of DH technology is the possibility of supplying house heating and domestic hot water to buildings located in sufficiently dense urban areas using efficient heat production instead of domestic boilers. Various types of plants can be connected to the same energy system, by means of pipelines installed in the ground [1]. This allows integrating a) renewable energy sources [2, 3], b) high performance technologies (such as various types of heat pumps [4,-6]), c) cogeneration plants [7, 8], and d) waste heat [9, 10].

The literature shows that this technology is fast evolving towards new management technologies; works in the literature show opportunities for reaching higher performance and flexibility [11-13]. Next DH generations are proposed and described in various paper [14-16] that highlight the potentials of DH to reach higher performance and diffusion, thanks to optimal integration with various energy sources.

However, real networks are often obsolete. This is particularly true when considering very large networks that have been built various decades ago. Modifications in these networks are usually not straightforward, especially when they are large [17-19]. In fact, changes in large networks require higher attention because of the more complex system management, the long distances involved, long transient due to the amount of water in the pipelines and a large variety of connected buildings.

One of the most important problems in DH system management is the presence of peak loads. This is particularly evident in Mediterranean areas, where heating systems are generally off during the night. Water in the building circuit cools down during the night because of the thermal losses. In the morning, when the heating systems are switched on, the thermal load dramatically increases, due to the necessity of increasing the temperature in the secondary circuit. Fig. 1 shows the thermal load profile for an entire DH network during a cold winter day in Mediterranean area. Fig. 1 shows that a significant peak occurs in the morning, that is partially fed by storages charged during the night (as can be noticed by negative thermal power values)

Effects of thermal peak occurrence are multiple. When thermal peaks occurs, if control is based on mass flow variation, the circulating mass flow at peak results as very high. This leads to: a) high pumping costs to supply water to the buildings in different areas, b) large water velocities in the pipelines, which increase the risks of failures, c) limitations in the additional buildings that can be connected to the network. In fact, during peaks, high velocities are reached in the pipelines (due to the large mass flow rates) and this makes impossible improve the pipeline exploitation to transport further mass flow rate. Although this limitation can be tackled by using proper management strategies based on fluid-dynamic models, as shown in [20], peak shaving can improve the situation. In case of malfunction, effects of thermal peaks may become significant. In fact, failures in pumps or in pipelines during peaks may create bottlenecks troublesome to be managed. In these occurrences, a smart management of failures by using proper control strategy [21] and methods for peak reduction are crucial in order to minimize the failure repercussions.

Another effect of thermal peaks is related to the necessity of a large use of the available heat production capacity. The use of heat-only boilers is usually required because the request exceeds that of the most efficient plants, such as cogeneration capacity. This increases the primary energy consumption of the DH system and its environmental impact.

A common approach for supplying thermal peaks concerns the installation of thermal storage [22-24]. This allows storing energy when the building demand is low (at night) and use it when the demand is high (in the morning). The use of thermal energy storage with the aim of reducing thermal peak is analyzed in [25]. The paper shows the potential of charging thermal storage in night and discharging it in the morning with the aim of shaving the peak load.

A different approach can be adopted in peak shaving. This concerns the application of demand response, which is a methodology developed in electric grids, that can be successfully applied to DH networks. This is often called virtual storage. Virtual storage consists in modifying the thermal demand profile of some buildings, acting on the settings of the heating system through modification of scheduling or control strategy. Previous analyses based on simulations show that significant peak reductions and decrease of primary energy consumption can be achieved [26-29].

In this paper, a real application of demand response on a real DH system is shown for the first time. It is shown that a peak reduction of about 5% can be achieved by anticipating the heat load delivery in some buildings. An optimization approach was used with the aim of minimizing the thermal peak load, obtaining the best rescheduling of the heating systems. The experimental tests were performed in a distribution network of the Turin DH system. Experimental tests are done by applying limitations to the maximum modifications in the building schedule and on the number of buildings subject to changes. A multi-scenario analysis is performed through a simulation approach to show the effects of demand response when these limitations are varied.

The paper is organized as follows. In Section 2 the application of demand response to DH system is discussed. The methodology followed is presented in Section 3, while results are reported in Section 4.

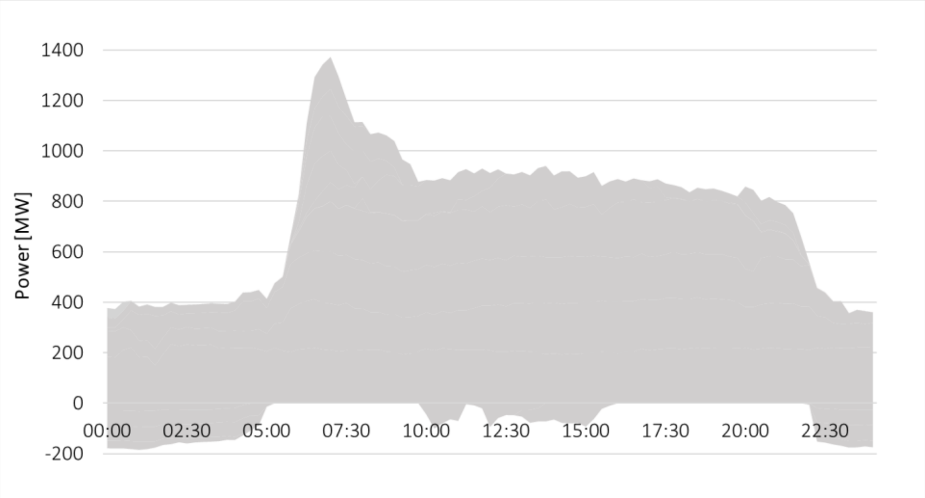


Figure 1. Thermal load evolution in a typical cold winter day for the Turin DH system

2. Application of demand response to DH networks

Demand response in DH systems has the aim of properly modifying the thermal request evolution. The reasons for varying the thermal load profile may be multiple:

1) Increase the incomes from electricity production by shifting the thermal load when the electricity cost is lower.
2) Possibility of selecting the most favorable plants, by shifting the thermal request to the time when these are available. This allows one reducing the fraction of heat produced by the less convenient plants and increase the fraction covered by renewable energy sources, waste heat and cogeneration.
3) Increase potentials for connection of additional buildings without modifying the pipeline, by making the request as flat as possible (this is particularly useful in case of control on mass flow rates).
4) Guarantee a variable load profile to increase the overall performance by means of time-varying management.
5) Allow reducing operational costs, such as the cost due to pumping systems, by reducing mass flow rates in some areas of the network during peak.
6) Reduce the impact of malfunctions to the buildings.

Demand response in district heating is also called virtual storage because it can provide some of the benefits of the storage but avoiding the investment costs and the necessity of a dedicated space for installation. The latter can be crucial in case of highly populated areas.
Virtual storage can be applied to DH by means of various procedures:

- modification of the heating schedule of buildings (Fig. 2). This consists in anticipating or delaying the anticipation time the heating systems installed in the buildings are switched on and off. Fig. 2 highlights the impact of the networks, which introduces delays in the propagation of the thermal demands. This means that the thermal load profile differs from the summation of the thermal demands of the buildings. Such effect can be captured using a thermos-fluid dynamic model of the network.
- modification in the substation settings. In substations two types of changes can be performed:
    - change in the substation control (such as in the outdoor compensation curve used to control the valve);
    - change in the control strategy, i.e. modification of the way the substation acts in the normal control or during special occurrence. In particular, it is possible to set values for the supply temperature, the difference between the primary and secondary return temperatures, etc.

In this work, the optimal schedules of heating system installed in the buildings was evaluated and applied on a real system. The aim of the work consists in the minimization of the thermal peak and thus obtain:

- an enhancement of the possibility to connect additional buildings to the network, since load adjustments are performed by varying the circulating mass flow rate;
- a decrease in boiler utilization, as a flatter load profile guarantees a higher flexibility in the selection of the operating plants;
- the possibility to reduce electricity production when its prices are low, and increase its production when prices are higher.

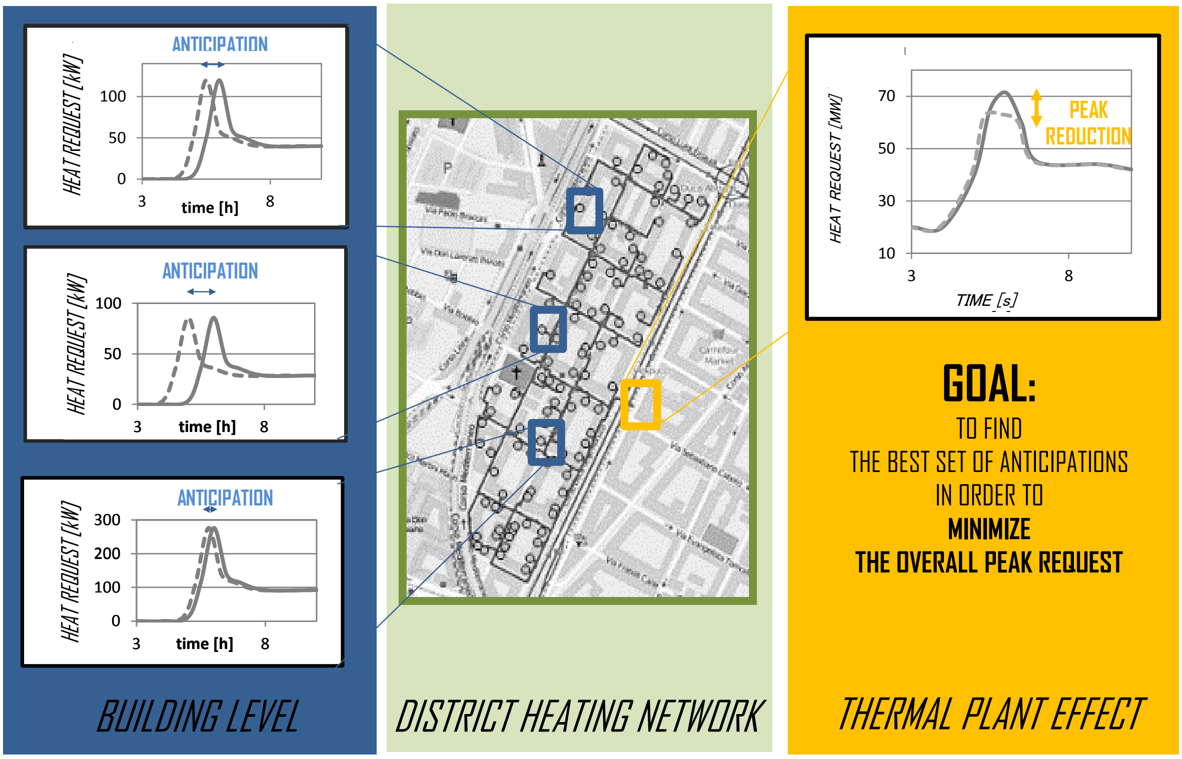


Figure 2. Demand response in DH system for thermal peak shaving: heating system rescheduling

3. Methodology description

The procedure followed for the evaluation of the demand response effects on a DH network is depicted in Fig. 3. This consists of 4 steps, which are detailed hereafter.

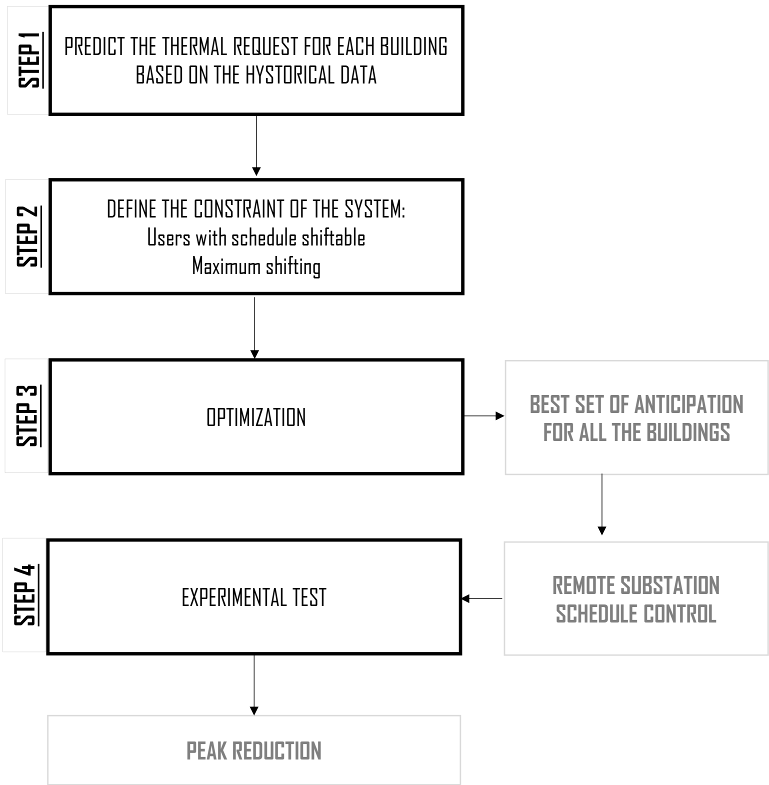


Figure 3. Schematic of the methodology followed

3.1 STEP 1. Prediction of the thermal demand of buildings

Data gathered at the DH substations and meteorological data were used to estimate the thermal demand evolution of the buildings. This piece of information is mandatory in order to obtain the optimal rescheduling. A system for the automatic data collection is installed in the substations. This is shown in Fig. 4, together with the main measurements available at the heat exchanger. Sensors for temperature and mass flow detection are installed at the inlet and at the outlet section. These data can be used in order to evaluate the demand profiles with different external temperatures, as shown in [30] and [31]. Evolution of the temperatures at the inlet and outlet sections, the mass flow rate on the primary side and the heat fluxes exchanged in various substations of a distribution network are reported in Fig. 4 for a typical winter day. Mass flow evolutions show that most of the heating systems are switched off during the night and switched on between 5 am and 6 am. This is the cause of the thermal peak in the total load.

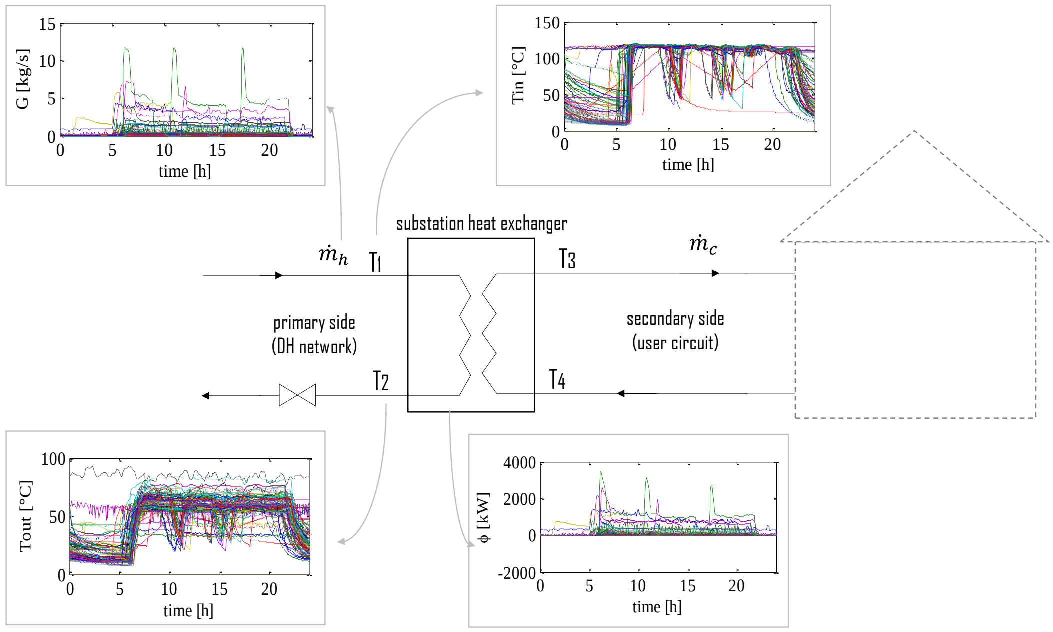


Figure 4. Schematic of a building substation and data collected

3.2 STEP 2. Definition of the optimization constraint

The independent variables of the optimization are the schedules of the heating systems, i.e. when they are switched on and off. The time modifications are discrete since the remote schedule control system may act with time step variations of 10 min. Some constraints are included in the optimization process:

- not all the heating systems can be subjected to schedule changes, but only public buildings and residential buildings which have signed a specific agreement with the DH company;
- in this first experimental analysis, only anticipations are considered; delays are not allowed. This is because delays may cause a lower indoor temperature in the morning, which might result in discomfort conditions;
- anticipations are limited to 20 minutes in order to avoid large effects on the indoor temperatures.

The experimental results obtained, complying with these limitations, are reported in Section 4.1. A specific analysis using building models should be performed in order to modify these constraints. In order to estimate benefits achievable by relaxing these constraint a numerical analysis has been performed, using the network physical model described in Section 3.3. Results obtained relaxing such constraints have been reported in Section 4.2.

3.3 STEP 3. Optimization process

Tab. 1 shows the optimization characteristics. The objective function to be minimized is the maximum value of the overall thermal request evolution; this lead to a shaving of the thermal peak as significant as possible. The independent variables are the anticipation of heat load delivery of the buildings connected to the network; this is a vector as long as the number of buildings. Since anticipation can be performed by discrete quantities, an integer-value optimization, in particular a heuristic approach, was used. Although this kind of optimization makes the procedure slower than in the case of a gradient based methods, it presents some advantages: a) it allows managing the non-linearity of the objective function; b) it allows one to get rid of possible local optima. In particular, a genetic algorithm (GA) has been selected. Such algorithm has been successfully applied in various different fields [32-34], dealing with both constrained and unconstrained problems.

The optimizer has the aim of finding the best set of anticipations of the heating system schedules which produces the best flattening of the total peak load. Anticipation was performed at building level (Fig. 2 left box), while the effect of the anticipation was evaluated at a global load, i.e. at a plant level (Fig. 2 right box). It is worth mentioning that global load at the plants is not the mere summation of the thermal requests in the buildings; this is due to the heat and mass transfer in the DH network (Fig.2 central box). This is mainly due to:

- Thermal losses between the pipelines.
- The time the water takes to reach the thermal plants from the buildings (heat advection).
- The water flowing the pipeline mixes with the other streams from other areas of the city at different temperatures; the temperature in a certain point depends on the mixing of the upstream flows.
- The thermal transients in the network, that are not negligible because of the large quantity of water within the pipelines.

In order to take into account these phenomena, a network physical model was included in the optimizer. This is a one dimensional network model, based on a graph approach [35]. The model solves mass, momentum and energy conservation equations applied to all the pipelines [36]. Momentum and mass equations are 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 thermal model is unsteady in order to consider the effects of demand variations on the water temperature distribution. Model validation is reported in [37].

As the supply temperature is kept constant during normal operation, only the return distribution network is studied on this work. This network connects 104 substations to the transport network. The test case is described in section 3.4. The boundary conditions imposed in the return network are:

- the entering mass flow rate is imposed in each node corresponding to the substations;
- the temperature of water entering the network in each substation is imposed.

Both quantities are taken from available measurements in the substations. The objective function is the maximum total load request by DH network, which is calculated as follows:

$$\Phi_{\mathrm{tot}}(\mathrm{t}) = \sum_{i=1}^{n\_plants} \mathrm{G}_{\mathrm{tot\_i}} \mathrm{c}_{\mathrm{p}} \left(\mathrm{T}_{\mathrm{supply\_i}}(\mathrm{t}) - \mathrm{T}_{\mathrm{return\_i}}(\mathrm{t})\right) \quad (1)$$

where G_{tot_i} is the total mass flow processed at the i_{th} thermal plant, and temperatures are the supply and the return temperature at the thermal plant.

Since for the experimental analysis a distribution network (DN) was considered, the effect of the demand response are evaluated on the point linking the distribution network to the transportation network. The heat flux to be minimized is expressed as:

$$\Phi_{\mathrm{tot}}(\mathrm{t}) = \mathrm{G}_{\mathrm{tot\_DN}} \mathrm{c}_{\mathrm{p}} \left(\mathrm{T}_{\mathrm{supply\_DN}}(\mathrm{t}) - \mathrm{T}_{\mathrm{return\_DN}}(\mathrm{t})\right) \quad (2)$$

where G_{tot_DN} is the total mass flow provided to the DN, $\mathrm{T}_{\mathrm{supply\_DN}}$ is the temperature at the node connecting the distribution network to the transport network on the supply line and $\mathrm{T}_{\mathrm{return\_DN}}$ is the temperature of the water exiting the distribution network and entering the transport network. The latter is evaluated by means of the network model.

The optimization process provides two pieces of information:

- The best anticipation time for each building heating system.
- The expected peak reduction.

Objective Function	$min\ (\Phi_{BCT}(t)_{max})$	*Maximum value of the daily request*
Independent variables	x_i	*Anticipation of the building schedule*
Constraints	x_{i_max}	*Maximum anticipation of the building schedule*
Method used	Heuristic	*Genetic algorithm*

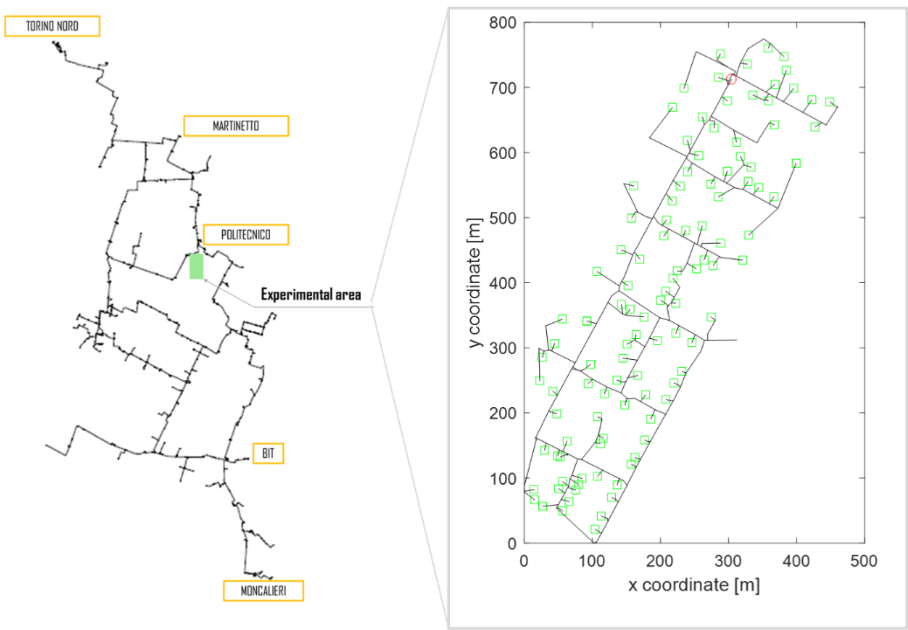
Tab. 1 Optimizer details

3.4 STEP 4. Experimental tests

In STEP 4, the optimal set of anticipations for the various buildings is applied to a distribution network of the Turin district heating system. The test was performed on the distribution network shown in Fig. 5. Both the location of the distribution network and the network topology are shown.

The Turin district heating system supplies heating to about 56 million m^3 of buildings (corresponding to about 6500 substations) Heat is generated in three large cogeneration plants and various heat-only boilers. Four large storage systems are also installed; these allow one increasing the heat fraction produced through cogeneration. The plant locations are indicated in the figure. The water supply temperature is constant at about 120°C while the return temperature is between 65 °C and 45 °C depending on the thermal load. Fig. 5a shows the transport network, which is the main pipeline connecting the plants with the various areas of the town. Additionally, 182 distribution networks connect the transport network to the buildings. These are not reported in Fig. 5a. One of the 182 distribution networks is the experimental domain of the test. This is shown in Fig. 5b. In particular, pipelines are reported in black, buildings are represented by green squares and the connection between the distribution network and the transport network is identified by a red circle. The area covered by the network is almost 900 m long and 300 m wide. This network supplies heat to 104 buildings.

During the experimental tests some constraints were imposed. One of these constraints is related to the number of buildings with variable schedule. In the case of the experimental test only 32 out of the 104 buildings have a schedule that can be modified, because of agreement reasons. The assignment of the anticipation time to the various buildings can be done by means of a remote control system. This was in the experimental tests to directly manage the scheduling of buildings. The maximum allowed anticipation was set to 20 minutes, in order to limit the effects on the indoor temperatures. The best anticipation for a building was applied and results obtained are discussed in the result section.



(a) (b)

Figure 5. Schematic of the test case: a) Turin transport network b) Distribution network used for the experimental test

4. Results

4.1 Experimental results

The experimental tests were performed in the distribution network used as test case. Three tests have been conducted in days with similar external temperatures (around 10 °C).The outcomes of the three tests conducted are reported in Fig. 6. The test conducted during the tree days are called Test1, Test 2 and Test 3. Fig. 6 shows a comparison of the total load in two different days: one is the day of the test (when the demand response was applied, respectively Test1, Test2 and Test3). The second is a day with the same meteorological conditions, , when the demand response was not applied (current condition, represented with the black curve). This allows one comparing which are the effects of the virtual storage on the total load of the distribution network. The significance of the comparison is due to the similarity of the request in the off-peak conditions (at 7 pm). In fact, the demand response only affects the thermal peak, while the thermal request after the peak (in steady state condition) should be the same in case of similar environmental temperature. The tests clearly show that in case demand response is applied the request is anticipated; in fact, the red dashed curve is shifted to the left. The maximum peak value was reduced in all the cases considered.

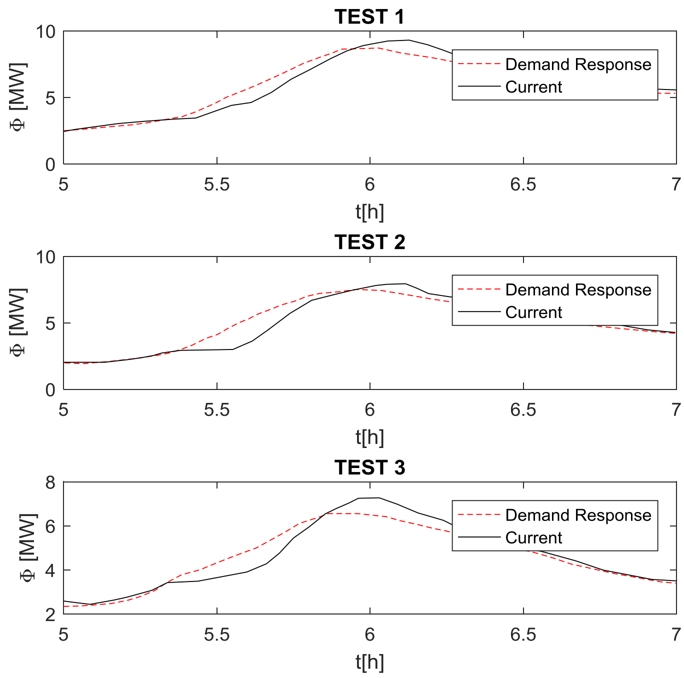


Figure 6. Thermal request evolution in case with and without demand response (comparison between similar days)

The maximum peak requests related to the experimental tests are shown in Fig. 7. In particular, the maximum peaks for the cases considered in Fig 6 are reported. Fig. 7a shows the maximum peak request, while Fig. 7b shows the peak reduction in the various tests. Peaks are higher in case of current conditions in all the tests. Peak reductions are always larger than 5%. This is an interesting result if considering that significant restrictions are applied in this case (maximum anticipation equal to 20 minutes and 30% of the buildings with variable schedule). On average, the peak is smaller when the external temperature increases; in particular, the night temperature significantly affects the following peak and also the peak reduction which can be achieved through rescheduling. In the case of test 2, the result on the peak reduction is also affected by the initial scheduling, which was slightly different for some of the buildings.

(a) (b)

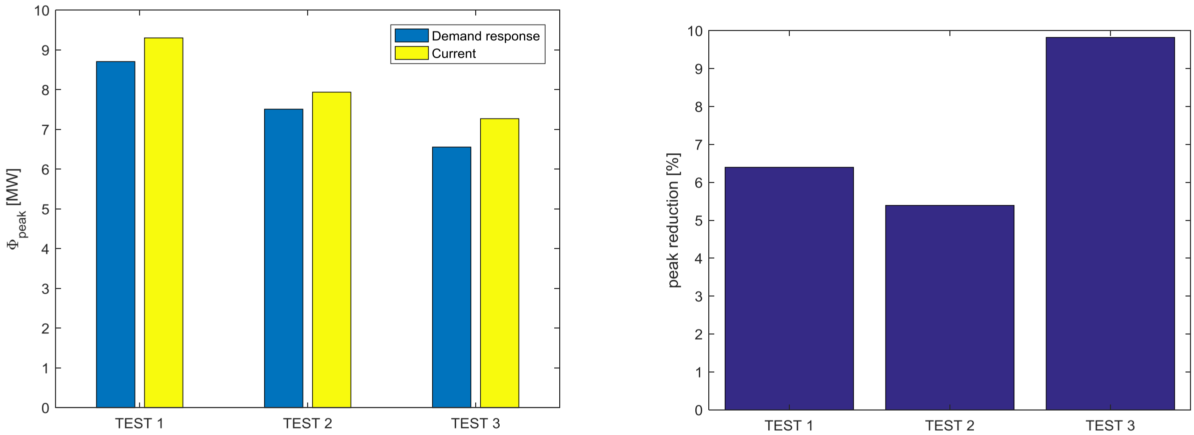


Figure 7. Comparison Demand response vs current condition. a) thermal peaks b) peak reduction

4.2 Multi-scenario analysis

It is important to remind that in the experimental tests two strong limitations have been respected: a) the maximum anticipation allowed is 20 minutes b) only a small fraction of building has a variable schedule. Authors consider that it is appropriate to test what are the effects of relaxing these limitations. In this section, results obtained by means of the simulation tool have been reported. Various simulations have been performed in different conditions. This gives a perspective of the benefits that can be obtained by using demand response in DH networks, in various conditions, exceeding the test cases.

The main two quantities affecting the thermal peak shaving achievable by demand response are a) the number of buildings that can be managed (with a heating system schedule that can be changed) and b) the maximum schedule modifications, i.e. the maximum anticipation that can be applied on a heating system schedule. For this reason, the simulation analysis was performed by considering various cases of:

- Number of buildings with variable schedule (from 30% to 100%).
- Maximum schedule modification (from 20 min to 90 min). The maximum antitipation which can be really applied to the substations should be verified using a proper model which takes into account the effects of thermo-physical characteristics of buildings on the indoor temperatures.

This analysis allows contextualizing the text case and allows giving a higher perspective of the potentials for the application of demand response in DH networks. Table 2 describes the variability considered for the two parameters highlighting the four extreme cases considered in the analysis.

		% variable buildings	
		min value **30%**	max values **100%**

maximum anticipation allowed	min value **20 min**	EXTREME CASE 1: more restricitve (small room for maneuver)	EXTREME CASE 2: several buildings small variation
	max value **90 min**	EXTREME CASE 3: few buildings large variation	EXTREME CASE 4: less restrictive (large room for maneuver)

Tab.2. Ranges considered for the multi-scenario analysis

Figure 8 shows the thermal profiles for the test case in current conditions and in case of demand response application. The four extreme cases, described in Tab. 2 are analyzed. Results show that the thermal peak occurs at about 6.15 a.m. Its value in current condition is larger than that in Fig. 6, due to a larger connection of buildings. In all the four cases, demand response produces a peak reduction. The load curve obtained with the demand response application is slightly shifted with respect to the current one because of the anticipations. Extreme case 1 is the case where the peak reduction is smaller; this is because of the small anticipation and low fraction of variable buildings. In case maximum anticipation or number of variable building increases (respectively CASE 2 and CASE 3) demand response has a more significant effect on the peak reduction. It is possible to notice that larger peak reductions can be achieved when the number of variable buildings increases, while the effect of maximum anticipation is limited when it is applied to a small percentage of buildings. Concerning the extreme case 4, which is the less restrictive, a large peak reduction is obtained. In this case, the peak is flattened and the request at the peak is similar to the request in off peak conditions. This means that when large anticipation and large number of variable building are considered demand response allows obtaining a complete thermal peak shaving.

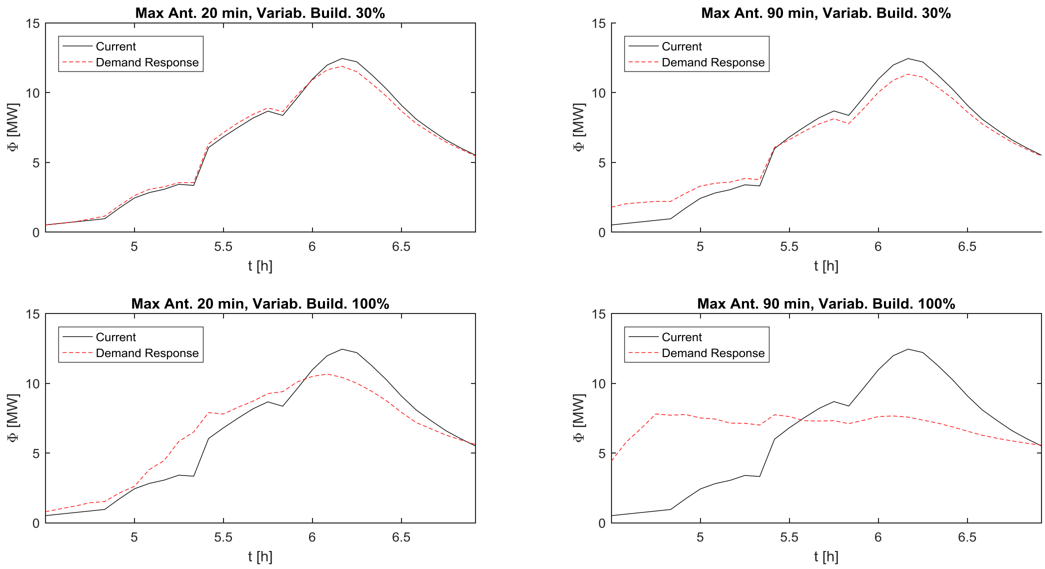


Figure 8. Evolution of thermal request with and without demand response in different conditions of a) maximum anticipation allowed b) number of variable building

Fig. 9 shows the results of the multi-scenarios analysis for different maximum anticipations allowed. The peak reduction is depicted varying the maximum anticipation allowed for the lowest and highest values of variable buildings (30% and 100%). Results are depicted in term of MW (left side of the figure), and percentage (right part of the figure).

In case of 30% of variable buildings, peak reduction ranges from 0.5 to 1.2 MW, corresponding to a 5-10% of maximum peak value. In case all the buildings can be modified (100% variable users) an higher peak reduction variability occurs in the range of cases considered. In this case, peak reduction ranges from 1.8 to 4.7 MW, corresponding to a 15-37% of peak reduction. This allows evaluating which are the effects that can be achieved by using demand response for thermal peak shaving with different conditions.

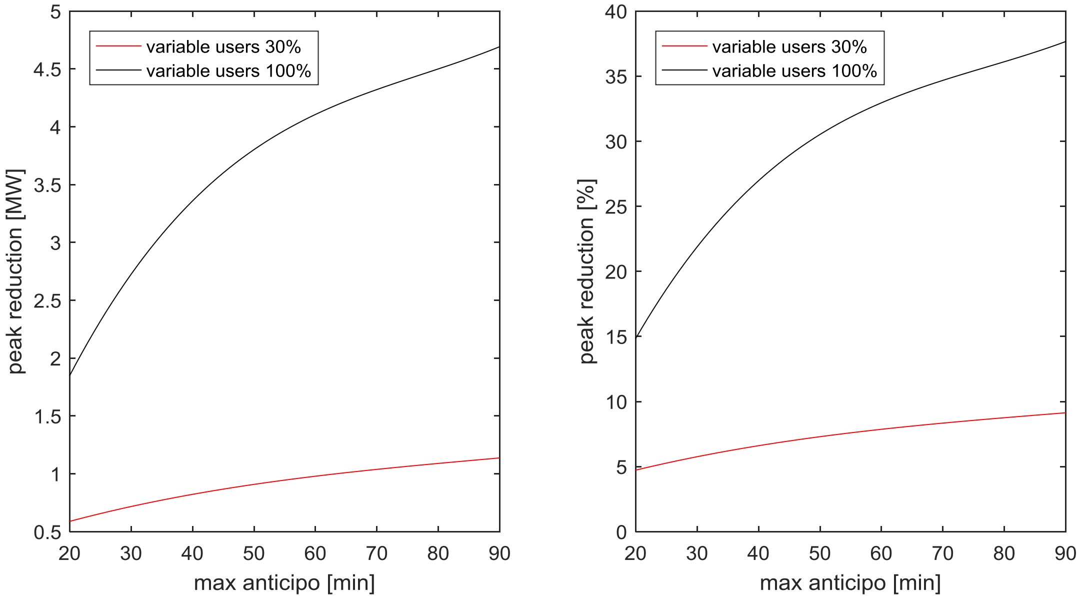


Figure 9. Peak reduction with demand response varying the maximum anticipation allowed

Fig. 10 shows a multi-scenarios analysis is performed for different percentage of buildings with variable schedule. The peak reduction is reported for both the smallest and largest allowed anticipation (20 min and 90 min). Results are depicted in term of MW (left figure), and percentage (right figure).

In case maximum anticipation is 20 min the peak reduction ranges from 0.5 to 1.7 MW, corresponding to 5-15%. In case of larger anticipation (90 min), a higher peak reduction variability occurs in the range of cases considered. In this case, peak reduction ranges from 1.1 to 4.7 MW, corresponding to a 9-37% of peak reduction. This allows estimating which are the effects that can be achieved by using demand response, increasing the number of buildings with a schedule that can be modified.

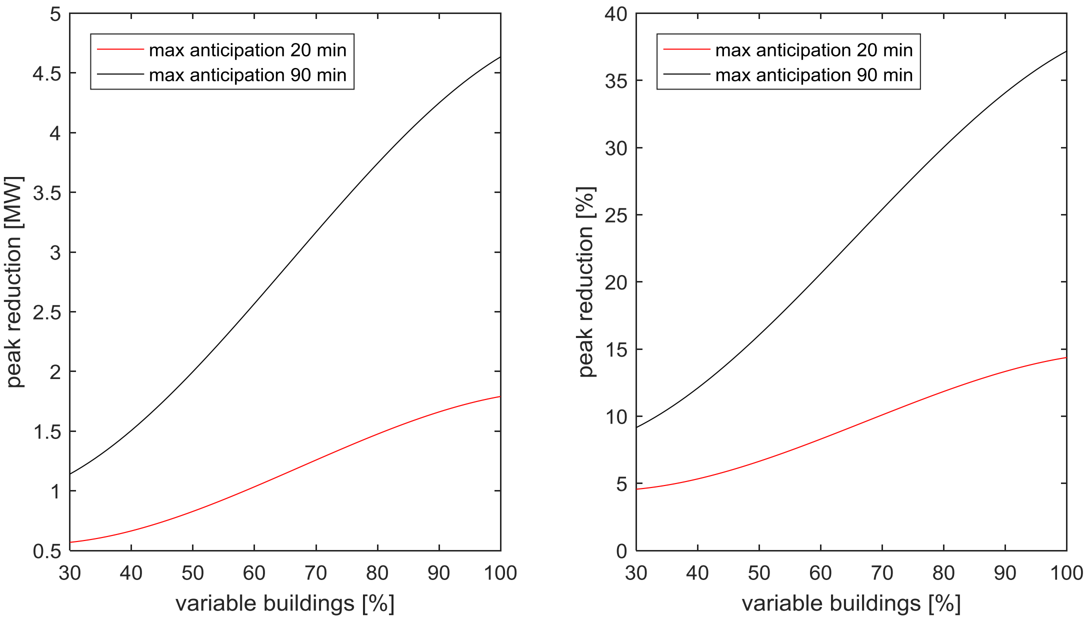


Figure 10. Peak reduction with demand response varying the percentage of variable buildings

4.3 Developments and improvements

It is worth mentioning that the limitation on the maximum anticipation allowed should be properly managed since it may cause non-negligible changes in the indoor temperature evolution. For this reason, it is proper to use a model to analyze the effects of schedule changes in the indoor conditions. This allows evaluating changes in the indoor conditions when some modifications are performed. A compact model of the building should be the proper way to evaluate these effects. This also allows considering delays in the switching on time or multiple pauses and attenuation. As an alternative, an experimental apparatus can be used to check the indoor condition modifications.
Results reported in the current paper consider only a distribution network. The effects of the demand response on a complete DH network are expected to be more effecting. In fact, distances involved when an overall network is considered are large and a properly selected anticipation for each building, or distribution network, can leads to a considerable thermal peak shaving.

5. Conclusions

In this paper, demand response (also called virtual storage) is shown to be applied to a real DH network for thermal peak shaving. Changes in schedules of heating systems installed in the buildings, is used for virtual storage application. A model has been created in order to achieve the optimal peak shaving. The model allows one evaluating the best rescheduling for the heating systems of the building installed in a network. An anticipation in the switching on time is used to reschedule users. Delays are not considered in order to not produce discomfort indoor conditions. The optimal rescheduling is performed by means of an optimization approach. The goal of the optimizer is to flatten the total thermal load as much as possible.

Rescheduling has been applied to a distribution network of the Turin DH system. Proper limitations were on the number of buildings which schedule can be modified and on the maximum anticipation. Experimental results shows that a non-negligible peak reduction can be achieved. Tests shows peak reduction of about 5%, despite the significant constraints that are applied.

A multi-scenario simulation analysis was performed in order to analyze the effects of demand response when limitations are relaxed. In particular, a) the number of building subjected to rescheduling and b) the maximum allowed anticipation have been varied in the analysis. Results shows that peak reduction ranges from 5% to more than 35%, depending on the scenario. Results are encouraging in the use of demand response in DH networks with the aim of changing the thermal request evolution for a better exploitation of the energy resources.

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