Investigating flexibility potential on district heating local thermal substations

Leonidas Zouloumis*
Department of Mechanical Engineering
University of Western Macedonia
Kozani, Greece
l.zouloumis@uowm.gr

Nikolaos Ploskas
Department of Electrical and Computer Engineering
University of Western Macedonia
Kozani, Greece
nploskas@uowm.gr

Giorgos Panaras
Department of Mechanical Engineering
University of Western Macedonia
Kozani, Greece
gpanaras@uowm.gr

***Abstract*— Recent decade research activity has focused on the reduction of the global building sector energy consumption since its contribution to the global primary energy consumption has been made known. Progress towards the optimal provision of heating load to buildings has been achieved with the implementation of district heating networks (DHN). The DHN flexibility is considered as a crucial factor to the evolution of thermal networks, as well as their decarbonization. This work investigates prospects on how thermal comfort intertwines with building parameters, such as thermal mass category and end-user heating power. The substation is exposed to different controlling strategies and peak-shaving scenarios. The simulations have uncovered a non-linear correlation between maximum peak-shaving potential of a substation and the discomfort of the end-user. Future work involves a more specific approach in peak-shaving potential identification and implementation of predictive controlling strategies and building surrogate model.**

***Keywords*— district heating, thermal network, flexibility, peak shaving, thermal comfort**

I. Introduction

Nowadays, there is a growing need for reduction of the consumed energy globally. The aspect of building energy consumption has been proven to play a major role in EU [1]. More specifically, it is stated that heating and cooling in building and industry sector accounts for half of the annual energy consumption [2]. Since the building sector has attracted research interest, actions have been taken to manage its energy consumption in a more efficient way, with the implementation of District Heating Network (DHN) systems. A DHN features a layout that enables the mass energy production and distribution to end-users (consumers). Throughout past decades, multiple generations of DHNs have been implemented, as they provide numerous advantages over local heating and cooling production, both in economic, as well as in an environmental manner [3-5]. Modern advancements in the thermal network sector include the promotion of the 4th generation [6, 7], as well as the 5th generation of DHN [6, 8]. One of the major benefits the 4th generation and 5th generation DHN offer, when compared to their predecessor (3rd generation) is the potential for Renewable Energy Sources (RES) implementation, as well as an operation temperature reduction that leads to lesser heat losses. Moreover the addition of RES enables the network energy production to be decentralized and distributed along the network. In other words, the 4th generation DHN development is an essential step towards decarbonization of energy systems [9].

However, DHN operation optimization comes along with certain issues that are to be coped with. Issues arise regarding proper DHN dimensioning while maintaining prospects for further expansion and addition of new users to the network [10]. Another matter is the existence of thermal capacity throughout the network and in the buildings. The thermal mass contained in the network can slow down the heat propagation in the network. This way, temperature changes in the network are associated with time intervals comparable to the change of heat load demand [11]. That means that a required heating load must be provided some time before the demand itself takes place. In other words, a means of heat load demand prediction is necessary and thus, demand-side management becomes a major subject that is being examined by the scientific community [12, 13].

A DHN feature that is characterized of great significance is the DHN flexibility. Research states that there are multiple approaches to the definition and quantification of a system flexibility [14 - 16] in the form of Performance Indicators (PI). Generally, in thermal systems it can be described as the ability of a system to change its operational load injection/ extraction speed by exploiting the variable thermal system power and adaptability speed [17], as well as thermal capacity of buildings/network/storages [18]. Regarding the variable thermal system power, it can either be referring to a single heat load producer (centralized co-generation power plants) that alters its provided heat load, or a set of multiple producers (decentralized multi-energy systems) that are coordinated to provide the heat demands. Since next-gen DHNs enable the use of multi-energy systems, efforts are focused on the latter, namely the effective multi-energy system optimization [19 – 22]. On the other hand, as stated before, the thermal mass in a DHN slows down heat propagation. At the same time, it also reduces temperature fluctuation due to various disturbances, such as heat load variation. Thermal mass also enables the storage of thermal energy, so that it can be utilized for heating at a later time, which in turn allows HVAC system controlling as another way enhancing DHN flexibility [23]. It is also stated that not only thermal mass, but insulation levels affect building potential as well [24]. This provides opportunities for heat load rescheduling [25]. Rescheduling heat production can be achieved in two ways: peak-shaving, as well as heat load shifting due to variable energy cost. There have been attempts to quantify the flexibility of a system in terms of heat load shifting [26]. Lastly, it should be stated that in some cases when the flexibility of a system is exploited, it also decreases and requires a time period to be recovered [27].

This research is financed by The Municipal Enterprise for water supply and sewerage of Kozani, Greece (DEYAK).

978-1-6654-6107-8/22/$31.00 ©2022 European Union

While it is evident that a DHN system has an inherent maximum amount of flexibility, due to the existence of variable load and thermal capacity, it can also be enhanced with the use of controlling strategies [16, 18, 23]. In literature, controlling strategies are divided into two main categories: reactive and predictive. Reactive (traditional) controlling strategies refer mostly to the conventional controlling systems. They usually control a system, through the current component measurements and react to the observed thermal system state and are characterized by simplicity of setup and operation. An example could be conventionally tuned PID controllers. Conversely, predictive (advanced) control strategies use component measurements in order to predict a future state of the system. Controllers using those strategies are able to predetermine the optimal control strategy to be implemented [28]. Numerous works [29-33] indicate MPC methods as an effective controlling strategy for DHNs, while certain works provide Genetic Algorithms (GA) [34] or Mixed Integer Linear Programming (MILP) [35, 36] methods for the same purpose. Despite the benefits predictive controllers may offer, there are also difficulties that accompany them, that mostly derive from the necessity of a reliable model of the existing system (be it a single consumer or a network of multiple consumers). There are multiple approaches to validating a thermal system model [11, 37], though it is referred that in some cases the occupant behavior and building related accuracy prediction is not considered in the models [38].

From the above, it is summarized that optimized DHN operation includes the implementation of advanced predictive controlling strategies to fully utilize its flexibility. Despite that, the literature focuses on thermal mass, that is considered a fixed characteristic in hourly operation of the system. It should be noted that an important factor that defines the flexibility potential is also occupant thermal comfort [39], that is subjective and dynamic. Thermal comfort is considered by the occupants to be the most important aspect of comfort [40]. Despite that, the value of thermal comfort for the flexibility identification of a building is not stressed enough in the literature.

The purpose of this work is to examine a DHN substation flexibility, when exposed to potential peak shaving scenarios. Moreover, a parametric simulation of a 24-hour building operation will be performed, examining how each parameter affects the system flexibility. Furthermore, prospects about a correlation between building flexibility potential and occupant thermal comfort will be examined.

II. Materials and Methods

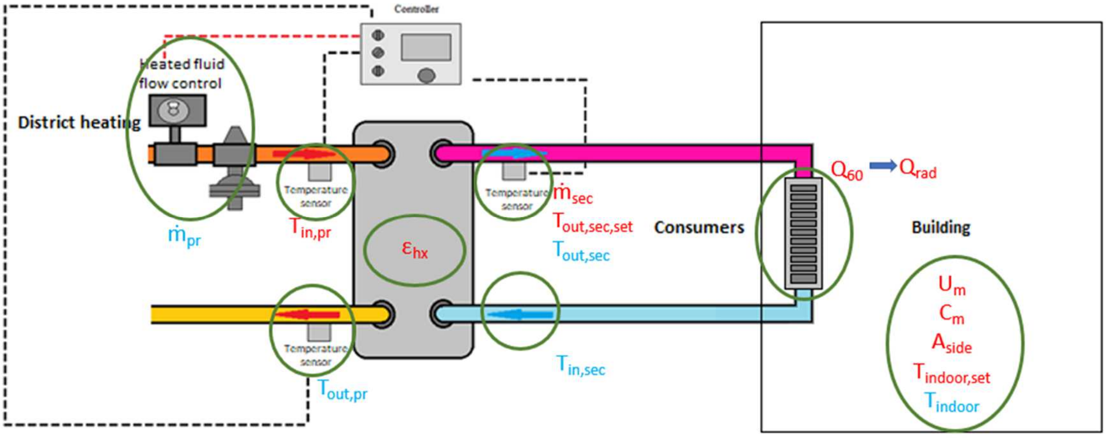


Fig.1 Schematic representation of the substation and the building - consumer

The main idea behind the parametric simulation that is performed is to expose different weight categories of buildings to various peak shaving scenarios and determine the ability of the system to maintain thermal comfort using the building thermal mass, the available heat load and its controlling strategy.

The system consists of a heating substation, along with a single-zone office that acts as a consumer. In the following figures a scheme of the DHN substation, along with the building-consumer, is presented (Fig. 1). The substation contains a heat exchanger that is responsible for transferring heat loads from the primary network (left side) to the secondary network (right side). Then the end-user radiator inside the building provides the heat loads to the building, ultimately heating the occupant zone. Table I displays all the system characteristics that are fixed over the scenarios, while Table II displays the scenario parameters.

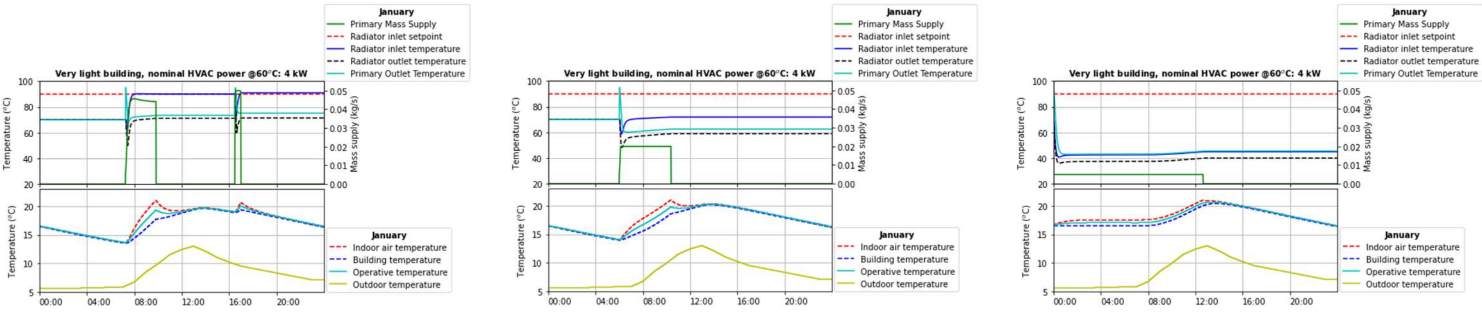
TABLE I. SUBSTATION CHARACTERISTICS AND PARAMETERS

Fixed parameters			
Symbol	**Description**	**Value**	**Unit**
$T_{in,pr}$	Heat exchanger, primary side inlet temperature	95	ºC
$T_{out,sec,set}$	Heat Exchanger, secondary side outlet temperature setpoint	90	ºC
U_m	Building average heat loss coefficient	0.7	W/(m²·K)
A_{side}	Building total side area	344	m²
$T_{indoor,set}$	Building indoor temperature setpoint	20	ºC
ε_{hx}	Heat exchanger efficiency	0.9	-

TABLE II. SUBSTATION CHARACTERISTICS AND PARAMETERS

Scenario parameters			
Symbol	**Description**	**Value**	**Unit**
$m_{pr,max}$	Maximum primary loop mass supply	0.03, 0.05	kg/s
m_{sec}	Secondary loop mass supply	0.03, 0.05	kg/s

C_m	Building heat capacity	80000 (Very light) 165000 (Medium) 360000 (Very heavy)	J/K
Q_{60}	Radiator nominal operation heating power @60 oC active temperature	2000, 4000	W



(a) (b) (c)

Fig.2 Daily substation and building operation for: a) 0% peak shaving, b) 60% peak shaving, c) 90% peak shaving.

Regarding the simulation models, the substation components operate using physical equations according to respective component models of TRNSYS [41]. The simulation of the substation is node-based, with its components essentially being linked to each other and transferring information about mass supply and temperature during each time step. On the other hand, the building model is constructed according to the EN ISO 13790 – simple hourly method [42]. Furthermore, the building model has been edited with linear interpolation equations that allows it to run in timesteps lower than one hour, as originally intended about the method. Thermal comfort is evaluated in discomfort degree hours, as previous work has shown that it provides more detailed results, when compared to the conventional binary comfort evaluation [43].

The building is exposed to environmental conditions that correspond to those of Kozani, Greece, during January. The occupancy period resembles that of a typical office building (09:00 – 17:00). Furthermore, the building indoor temperature setpoint is 20 ºC, while occupants are at thermal comfort when indoor temperature is above 19 ºC. The parametric simulation lasts for 24 hours in each scenario, with a time step of 1 minute. A time step of this scale ensures that the substation reacts quickly to indoor temperature changes. Moreover, it is necessary that a short time step be used, as building temperature changes also affect the operation of the substation.

The scenarios that will take place are presented below:

- Conventional heating schedule
- 30% peak shaving schedule
- 60% peak shaving schedule
- 90% peak shaving schedule
- Preheat schedule
- Preheat schedule with 30% peak shaving
- Preheat schedule with 60% peak shaving
- Preheat schedule with 90% peak shaving

Regarding the control strategies, as far as the conventional schedule is concerned, the substation operates only during the occupancy period and prevents the indoor temperature to fall below thermal comfort levels. The preheat control strategy differs only at the fact that the substation will attempt to operate some time before the occupancy periods, so that thermal comfort is achieved from the start of the occupancy time period. The controller simulates turning itself on earlier and repeats this process until it finds the ideal time to turn on the substation operation. This way, no thermal energy is wasted by excessively preheating the indoor air. The presented preheating strategy has been used in previous work [44] and focuses on occupant comfort optimization.

Finally, the scenarios will be repeated for two radiator nominal operation heating power levels, as indicated in Table II, for each building weight category. It is noted that maximum primary loop mass supply is set according to the radiator power. Namely, for nominal radiator power of 2 kW, the maximum primary mass supply is set to 0.03 kg/s, while for the case of 4 kW, 0.05 kg/s maximum power supply is used. The secondary mass supply does not vary during the simulation and has the same value as the maximum primary mass supply.

III. Results

Results from the methodology are displayed in this section. To begin with, for indicative purposes, Fig. 2 presents the dynamic daily simulation of the substation and the building, using the preheat strategy. The substation is exposed to different peak shaving scenarios and attempts to satisfy the thermal comfort in the building, by shifting the heating schedule earlier in the day and essentially preheating the indoor air.

As observed from Fig.2a, when no peak shaving is applied, the controller uses the preheat strategy to achieve thermal comfort at 09:00 and thus, turns on the heating at 07:30. When applying 60% peak shaving (reducing maximum primary mass supply to 0.02 kg/s), the controller decides to turn the heating on even earlier, at about 06:00. As a result, thermal comfort is still attained at 09:00. On the contrary, in the case of 90% peak shaving, despite the efforts of the controller to preheat the building from the start of the simulation, thermal comfort is attained at 11:00. That means occupants are exposed to 2 hours of discomfort. It can be inferred that the maximum peak shaving capability for the specific building is between 60% and 90%, when user comfort requirements for the indoor air are above 19 ºC. By applying different peak shaving scenarios, an exact peak shaving capability may be determined.

By examining the case of operation using 4 kW radiator (Fig. 4), it is initially observed that thermal discomfort is at

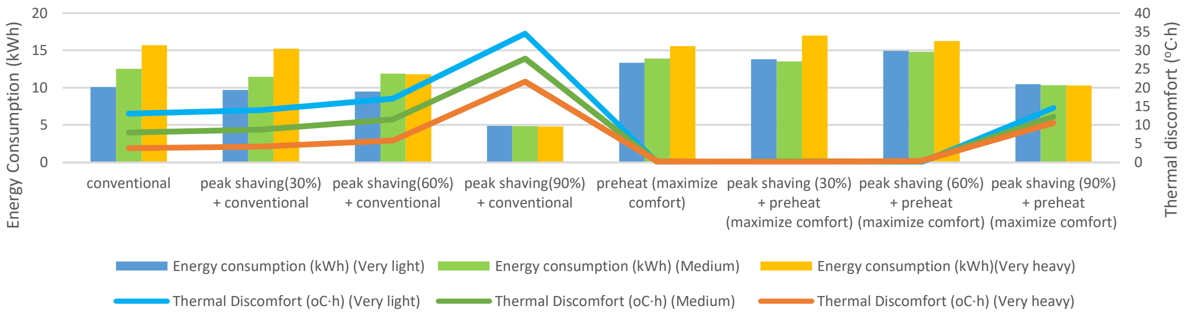


Fig.3 Energy consumption and thermal discomfort for buildings with 2 kW radiator

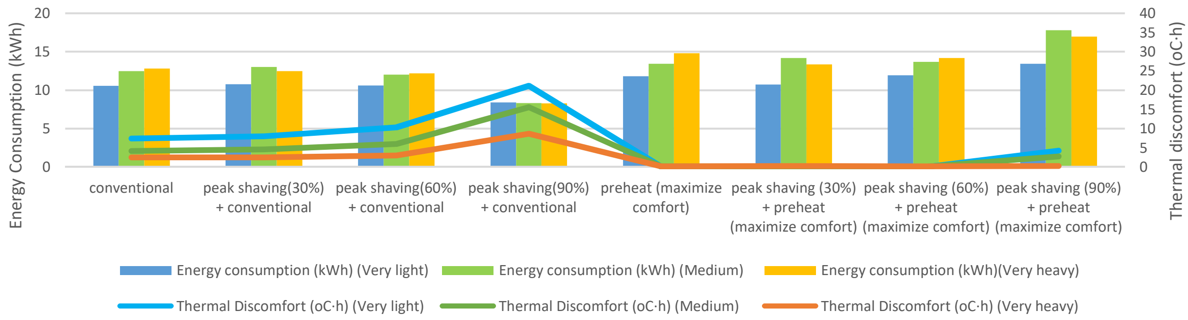


Fig.4 Energy consumption and thermal discomfort for buildings with 4 kW radiator

In the next part of the section graph containing the energy consumption and thermal discomfort results, during each of the scenario runs, is presented (Fig. 3), for the 2 kW radiator case. It can be deduced that comfort levels are more easily maintained in the case of a very heavy building, when compared to the very light or medium case. This is because by increasing thermal mass, temperature variation is reduced and can be maintained at a higher level, and thus closer to the comfort zone. Moreover, in the conventional schedule scenarios, peak shaving is expectedly reducing thermal comfort levels. A very interesting note is that while applying progressively a stricter limit on primary thermal mass supply via peak shaving (in steps of 30% of the original maximum primary thermal mass supply) the thermal discomfort increase follows a non-linear pattern. Regarding the preheat scenarios, it is evident that the preheat controlling strategy by itself has decreased thermal discomfort levels in all building categories. Moreover, it allows for a larger peak-shaving strategy, as comfort does not deteriorate as much. Namely, preheat strategy with 90% peak shaving provided with discomfort ratings similar to those of the conventional strategy with 60% peak shaving. That means a simple preheat allows for a 30% increase in peak-shaving actions.

As far as energy consumption is concerned, peak shaving tends to lead to slightly lower consumptions in the conventional case. However, no linear or non-linear correlation can be distinguished about this effect, so further examination should take place. The energy consumption in the preheat case does not follow a standard reduction trend, as well. Despite that, extreme peak shaving (reduction in maximum mass supply by 90%) tends to lower energy consumption by a notable margin, which is increased per building category.

lower levels, especially for the very light and medium building categories. In addition, there is not a clear sign about the energy consumption change. What is also intriguing is that the while consumption appears to have increased overall, when compared to the case of the 2 kW radiator, there is an exception in the very heavy building case, which provides opposite results in low peak shaving scenarios. The non-linear correlation between the peak-shaving intensity and thermal discomfort remains, despite having a smoother curve.

IV. Conclusions

In this paper, the peak-shaving prospects of a single-zoned office building are examined, when acting as a consumer of a DHN. The results indicate that the flexibility of a building is analogous to the building weight category. Moreover, each building has a distinct potential to withstand peak-shaving strategies implemented by the DHN, beyond which the occupant comfort levels are compromised. In the case of this work, buildings could maintain comfortable temperature conditions for peak shaving levels ranging up to approximately 60%. That being said, this flexibility potential can be further improved, up to a certain degree, by implementing preheat controlling strategies. Case results showed a simple preheat is able to increase peak shaving potential of a building by 25% without reducing comfort levels below those of the conventional heating strategy. Maximum flexibility potential is a valuable information for calculating the minimum heat demand of a district network, in case of a heat load energy production reduction. This will also be a great tool for optimally providing heat loads that are produced by RES, making their unpredictability in heat load production more manageable. That will help DHNs to be decarbonized in a more decisive manner.

Currently, there are some limitations in this work. First of all, the creation of a building model used in this work cannot be used in a real controller due to its complexity and computational power requirements, that BES controllers may not possess. Furthermore, the simulation took place using a single consumer, which does not correspond in the real, multi-consumer networks. Moreover, a flexibility PI needs to be implemented in the present case, that could describe the peak shaving limits that each building is able to withstand, correlating it with occupant comfort requirements. In addition, no definite answers have derived from the energy consumption results of each case. That means that the implemented preheating strategy does not opt for minimized energy consumption. An interesting subject would be a redesigning of the system components to maximize the peak-shaving capabilities. Lastly, peak-shaving optimization could be performed by a predictive controlling algorithm.

REFERENCES

[1] Eurostat Energy Statistics—An Overview. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_statistics_-an_overview#Primary_energy_production (accessed on 26 July 2022).

[2] European Commission, "Towards a smart, efficient and sustainable heating and cooling sector". Brussels, 2016. Available online https://ec.europa.eu/commission/presscorner/detail/en/MEMO_16_311 (accessed on 26 July 2022).

[3] Werner, S. (2017). International review of district heating and cooling. *Energy*, *137*, 617–631. https://doi.org/10.1016/J.ENERGY.2017.04.045

[4] Rezaie, B., & Rosen, M. A. (2012). District heating and cooling: Review of technology and potential enhancements. *Applied Energy*, *93*, 2–10. https://doi.org/10.1016/j.apenergy.2011.04.020

[5] Persson, U., & Werner, S. (2011). Heat distribution and the future competitiveness of district heating. *Applied Energy*, *88*(3), 568–576. https://doi.org/10.1016/J.APENERGY.2010.09.020

[6] Lund, H., Østergaard, P. A., Nielsen, T. B., Werner, S., Thorsen, J. E., Gudmundsson, O., Arabkoohsar, A., & Mathiesen, B. V. (2021). Perspectives on fourth and fifth generation district heating. *Energy*, *227*, 120520. https://doi.org/10.1016/j.energy.2021.120520

[7] Averfalk, H., & Werner, S. (2020). Economic benefits of fourth generation district heating. *Energy*, *193*. https://doi.org/10.1016/j.energy.2019.116727

[8] Bilardo, M., Sandrone, F., Zanzottera, G., & Fabrizio, E. (2021). Modelling a fifth-generation bidirectional low temperature district heating and cooling (5GDHC) network for nearly Zero Energy District (nZED). *Energy Reports*, *7*, 8390–8405. https://doi.org/10.1016/J.EGYR.2021.04.054

[9] Connolly, D., Lund, H., Mathiesen, B. V., Werner, S., Möller, B., Persson, U., Boermans, T., Trier, D., Østergaard, P. A., & Nielsen, S. (2014). Heat Roadmap Europe: Combining district heating with heat savings to decarbonise the EU energy system. *Energy Policy*, *65*, 475–489. https://doi.org/10.1016/J.ENPOL.2013.10.035

[10] 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. https://doi.org/10.1016/j.jclepro.2018.08.272

[11] del Hoyo Arce, I., López, S. H., Perez, S. L., Rämä, M., Klobut, K., & Febres, J. A. (2018). Models for fast modelling of district heating and cooling networks. *Renewable and Sustainable Energy Reviews*, *82*, 1863–1873. https://doi.org/10.1016/j.rser.2017.06.109

[12] Cai, H., Ziras, C., You, S., Li, R., Honoré, K., & Bindner, H. W. (2018). Demand side management in urban district heating networks. *Applied Energy*, *230*, 506–518. https://doi.org/10.1016/J.APENERGY.2018.08.105

[13] Guelpa, E., Marincioni, L., Deputato, S., Capone, M., Amelio, S., Pochettino, E., & Verda, V. (2019). Demand side management in district heating networks: A real application. *Energy*, *182*, 433–442. https://doi.org/10.1016/J.ENERGY.2019.05.131

[14] Reynders, G., Amaral Lopes, R., Marszal-Pomianowska, A., Aelenei, D., Martins, J., & Saelens, D. (2018). Energy flexible buildings: An evaluation of definitions and quantification methodologies applied to thermal storage. *Energy and Buildings*, *166*, 372–390. https://doi.org/10.1016/J.ENBUILD.2018.02.040

[15] Lopes, R. A., Chambel, A., Neves, J., Aelenei, D., & Martins, J. (2016). A Literature Review of Methodologies Used to Assess the Energy Flexibility of Buildings. *Energy Procedia*, *91*, 1053–1058. https://doi.org/10.1016/j.egypro.2016.06.274

[16] Clauß, J., Finck, C., Vogler-Finck, P., & Beagon, P. (2017). Control strategies for building energy systems to unlock demand side flexibility – A review. *12th International Conference of IBPSA (Building Simulation 2017) San Francisco, US.* https://www.researchgate.net/publication/324877113

[17] Bessa, R., Moreira, C., Silva, B., & Matos, M. (2014). Handling renewable energy variability and uncertainty in power systems operation. *Wiley Interdisciplinary Reviews: Energy and Environment*, *3*(2), 156–178. https://doi.org/10.1002/wene.76

[18] Vandermeulen, A., van der Heijde, B., & Helsen, L. (2018). Controlling district heating and cooling networks to unlock flexibility: A review. *Energy*, *151*, 103–115. https://doi.org/10.1016/j.energy.2018.03.034

[19] Wang, Y., You, S., Zhang, H., Zheng, W., Zheng, X., & Miao, Q. (2017). Hydraulic performance optimization of meshed district heating network with multiple heat sources. *Energy*, *126*, 603–621. https://doi.org/10.1016/j.energy.2017.03.044

[20] Ghilardi, L. M. P., Castelli, A. F., Moretti, L., Morini, M., & Martelli, E. (2021). Co-optimization of multi-energy system operation, district heating/cooling network and thermal comfort management for buildings. *Applied Energy*, *302*, 117480. https://doi.org/10.1016/J.APENERGY.2021.117480

[21] Guelpa, E., Bischi, A., Verda, V., Chertkov, M., & Lund, H. (2019). Towards future infrastructures for sustainable multi-energy systems: A review. *Energy*, *184*, 2–21. https://doi.org/10.1016/J.ENERGY.2019.05.057

[22] di Somma, M., Yan, B., Bianco, N., Graditi, G., Luh, P. B., Mongibello, L., & Naso, V. (2017). Multi-objective design optimization of distributed energy systems through cost and exergy assessments. Applied Energy, 204, 1299–1316. https://doi.org/10.1016/J.APENERGY.2017.03.105

[23] Péan, T. Q., Salom, J., & Costa-Castelló, R. (2019). Review of control strategies for improving the energy flexibility provided by heat pump systems in buildings. Journal of Process Control, 74, 35–49. https://doi.org/10.1016/j.jprocont.2018.03.006

[24] le Dréau, J., & Heiselberg, P. (2016). Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy*, *111*, 991–1002. https://doi.org/10.1016/J.ENERGY.2016.05.076

[25] 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. https://doi.org/10.1016/j.energy.2017.06.10

[26] Lopes, R. A., Chambel, A., Neves, J., Aelenei, D., & Martins, J. (2016). A Literature Review of Methodologies Used to Assess the Energy Flexibility of Buildings. *Energy Procedia*, *91*, 1053–1058. https://doi.org/10.1016/j.egypro.2016.06.274

[27] Chen, L., Xu, Q., Yang, Y., & Song, J. (2021). Optimal energy management of smart building for peak shaving considering multi-energy flexibility measures. *Energy and Buildings*, *241*, 110932. https://doi.org/10.1016/J.ENBUILD.2021.110932

[28] Gholamzadehmir, M., del Pero, C., Buffa, S., Fedrizzi, R., & Aste, N. (2020). Adaptive-predictive control strategy for HVAC systems in smart buildings – A review. *Sustainable Cities and Society*, *63*, 102480. https://doi.org/10.1016/j.scs.2020.102480

[29] Saletti, C., Zimmerman, N., Morini, M., Kyprianidis, K., & Gambarotta, A. (2022). A control-oriented scalable model for demand side management in district heating aggregated communities. *Applied Thermal Engineering*, *201*. https://doi.org/10.1016/j.applthermaleng.2021.117681

[30] Saloux, E., & Candanedo, J. A. (2021). Model-based predictive control to minimize primary energy use in a solar district heating system with seasonal thermal energy storage. *Applied Energy*, *291*, 116840. https://doi.org/10.1016/j.apenergy.2021.116840

[31] de Lorenzi, A., Gambarotta, A., Morini, M., Rossi, M., & Saletti, C. (2020). Setup and testing of smart controllers for small-scale district heating networks: An integrated framework. *Energy*, *205*. https://doi.org/10.1016/j.energy.2020.118054

[32] Zimmerman, N., Kyprianidis, K., & Lindberg, C. F. (2019). Achieving lower district heating network temperatures using feed-forward MPC. *Materials*, *12*(15). https://doi.org/10.3390/ma12152465

[33] Birk, W., Atta, K. T., & Uden, F. (2019). Improving district heating system operation through control configuration selection and adaptive control. *2019 18th European Control Conference, ECC 2019*, 2944–2949. https://doi.org/10.23919/ECC.2019.8795742

[34] Fang, T., & Lahdelma, R. (2015). Genetic optimization of multi-plant heat production in district heating networks. *Applied Energy*, *159*, 610–619. https://doi.org/10.1016/j.apenergy.2015.09.027

[35] Kouhia, M., Laukkanen, T., Holmberg, H., & Ahtila, P. (2019). District heat network as a short-term energy storage. *Energy*, *177*, 293–303. https://doi.org/10.1016/j.energy.2019.04.082

[36] Leśko, M., Bujalski, W., & Futyma, K. (2018). Operational optimization in district heating systems with the use of thermal energy storage. *Energy*, *165*, 902–915. https://doi.org/10.1016/j.energy.2018.09.141

[37] Tardioli, G., Narayan, A., Kerrigan, R., Oates, M., O'Donnell, J., & Finn, D. P. (2020). A methodology for calibration of building energy models at district scale using clustering and surrogate techniques. *Energy and Buildings*, *226*. https://doi.org/10.1016/j.enbuild.2020.110309

[38] Talebi, B., Mirzaei, P. A., Bastani, A., & Haghighat, F. (2016). A Review of District Heating Systems: Modeling and Optimization. Frontiers in Built Environment, 2. https://doi.org/10.3389/fbuil.2016.00022

[39] ANSI/ASHRAE. ANSI/ASHRAE Standard 55-2020, Thermal Environmental Conditions for Human Occupancy; American Society of Heating, Refrigerating and Air Conditioning Engineers: Atlanta, GA, USA, 2020.

[40] Frontczak, M., & Wargocki, P. (2011). Literature survey on how different factors influence human comfort in indoor environments. *Building and Environment*, *46*(4), 922–937. https://doi.org/10.1016/j.buildenv.2010.10.021

[41] Klein, S.A. et al, 2017, TRNSYS 18: A Transient System Simulation Program, Solar Energy Laboratory, University of Wisconsin, Madison, USA

[42] International Standard Organization. ISO 13790-2008, Energy Performance of Buildings, Calculation of Energy Use for Space Heating and Cooling; ISO: Geneva, Switzerland, 2008.

[43] Zouloumis L, Stergianakos G, Ploskas N, Panaras G. Dynamic Simulation-Based Surrogate Model for the Dimensioning of Building Energy Systems. Energies. 2021; 14(21):7141. https://doi.org/10.3390/en14217141

[44] Zouloumis L., Panaras G. (2021), Development of a Smart Thermostat. IAQ 2020: Indoor Environmental Quality Performance Approaches. 4-6 May, Athens, Greece