Model predictive control for heat flexibility activation of the Thermally Activated Building System

Dingzhou Liu[1,2], Xiaochen Yang[1,2], Wenze Guan[1,2],Zhe Tian[1,2],Yi Zong[3]
[1]School of Environmental Science and Engineering, Tianjin University, Tianjin, China
[2]Tianjin Key Laboratory of Built Environment and Energy Application, Tianjin University, Tianjin 300072, China
[3]Division for Power and Energy Systems, Department of Wind and Energy Systems, Technical University of Denmark, Denmark

Abstract

The Thermally Activated Building System (TABS) can provide high thermal comfort level and utilize the low temperature energy resources efficiently. And it has great energy flexibility which offers the possibility of load shifting. However, the large building thermal mass of the TABS systems also provides many challenges for indoor temperature control. In order to minimize the costs and maximize the utilization of energy flexibility, an economic model predictive control (EMPC) strategy is developed by the authors and applied to the TABS system of a near-zero energy building in Tianjin. And compared with the RBC control strategy.The results show that EMPC has a lower energy price cost.

Highlights

- Economic model predictive control
- Rule-based control
- Thermally Activated Building System

Introduction

Thermally Activated Building System (TABS) uses the hydronic pipes inside the building structural elements with the warm/cooled water circulating inside to change the heating/cooling load on the demand side. Due to the large thermal capacity of building mass, TABS can be used as thermal energy storage (TES) systems to perform load shifting and peak shaving, which results in better energy efficiency and economy. Moreover, TABS can also provide more comfortable indoor climate concerning the more uniform heat distribution, the lower temperature difference between the supply and comfort level, and no draft due to the ventilation[1]. However, the large thermal inertia of TABS also hinders the fast response to the internal/external disturbances, which need to be addressed before its wide application.

This paper uses Dymola software to simulate a typical low-energy residential building in Tianjin, which using the electrical heat pumps for energy supply. The Economic Model Predictive control(EMPC) strategy that considers the indoor occupancy, indoor thermal comfort temperature, and dynamic electricity price is developed, so to maximize the utilization of the flexible heat potential of TABS and to minimize the overall energy expenses[2].On the co- simulation platform, the performance of the EMPC controller is simulated and assessed from the view of thermal comfort, energy consumption, and electricity cost. In order to create a more realistic stochastic model that takes into account the uncertainty of the input variables, the grey box model of the building was identified by the measured data from the actual case study. Secondly, a cost-effective mixed integer linear programming problem (EMPC) controller is created for the TABS system. In order to estimate the immeasurable variables and remove noise from the measured values, a Kalman filter is utilized. Thirdly, a co-simulation experiment was run to empirically explore various control strategies under a range of climatic conditions and the practical tiered power prices. Last but not least, the TABS performances under the EMPC were compared to conventional RBC strategy, so to characterize the improvement.

Method

Framework of RBC and EMPC for TABS system

Rule-based control (RBC)[3] is the execution of a specific signal or action when certain specified conditions are satisfied. The development of RBC in this paper considers the indoor thermal comfort temperature, indoor occupancy, and local policy for time-of-day electricity pricing.The specific control strategy is illustrated in 2-1(a)-(d), The range of indoor thermal comfort temperature is determined by GB 50736-2012. In winter, the design temperature of indoor heating in severe and cold areas should be 18 ℃ -24 ℃ [4]. As shown in Figure 2-1(a), central heating in Tianjin is implemented with a tiered electricity price. Peak-valley periods are divided into: 23:00 to 7:00 trough periods; 7:00-8:00, 11:00-18:00; Peak hours: 8:00-11:00 and 18:00-23:00. The occupancy rate of the residential building assumes that the user goes out to work at 8:00 AM, returns home at 18:00 PM, and stays at home from 18:00 PM to 8:00 am the next morning, as shown in Figure 2-1(b). Figure 2-1(c) shows the dynamic setting temperature of the room. From 0:00-8:00, the electricity price is low price period and segment period. At this time, the frequency conversion valve of the heat pump is opened to maintain the room temperature at 22℃. From 8:00 to 11:00, the electricity price is high and the user is not in the room. In this case, the room temperature should be kept at least 18℃ below the minimum thermal comfort temperature of human body. From 11:00 to 18:00, the electricity price is in the normal period, and the frequency conversion valve is opened. Although the occupancy of the room is 0 during this period, in order to reduce the peak pressure during the peak period, the

https://doi.org/10.26868/25222708.2023.1343

preheating is implemented in advance for a period of time, and the room temperature is maintained at the upper limit of the indoor thermal comfortable temperature of 24℃ to reserve energy for use during the peak period. From 18:00-23:00, as the electricity price is at its peak, the indoor temperature can be maintained at 20℃. From 23:00 to 24:00, when the electricity price is at a low point, the variable frequency valve is opened and the room is maintained at 22℃.

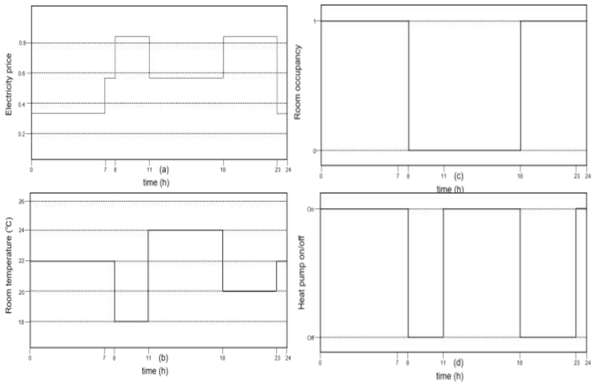

Figure 2-1 (a)Tiered electricity price (b)Indoor occupancy (c)Room temperature (d)Heat pump on/off

In order to deal with the long time response of TABS due to the large thermal inertia, the economic model predictive control (EMPC) method was developed in this study. The basic operational flow of the EMPC with this paper is shown in Figure 2-2, as the main objective of the EMPC in this study is to minimize the overall energy cost. The gray box model of the measured low-energy building is established for the heat load prediction. To reflect the actual case as much as possible, the measured historical data of the heating system and outdoor environment are used for the model identification. The disturbance variables of the outdoor air dry bulb temperature, solar radiation, and soil temperature are considered for the prediction of the heat load of the case study in the prediction horizon. The EMPC is supposed to minimize the cost of heating while maintaining the indoor temperature within the comfort range by regulating the operation of the heat pump. The heat supply control sequence is then generated by the rolling optimization when the economic cost of the goal function is minimized during the forecast phase (Np). In order to assure the accuracy of the prediction, the Kalman filer is applied to correct the difference between the real and forecast values.

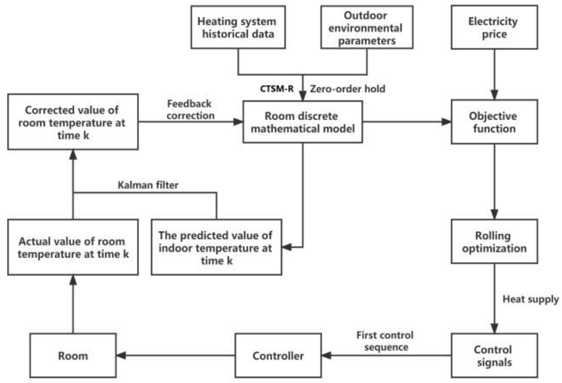

Figure 2-2 Flow chart of EMPC of the case study

RC-based grey box model of the case study

The authors created a grey-box model of the case study, which in this article uses the RC first-order model technique, as shown in Figure 2-3, and it primarily consists of four parts: the external environment, the building's ordinary envelope, the internal environment, and the TABS slab. Because the building envelope is mostly made up of two components—transparent windows and opaque walls. The heat transfer between the indoor air and the heated floor's inner surface, the building's envelope's inner surface, and the outside air through the windows is represented by one node for simplicity. The temperature of the water inside the embedded pipe, the thermal resistance from the pipe's upper surface to the heated floor's upper surface, and the thermal resistance from the pipe's lower surface to the earth compose the floor heating model. Considering the Gaussian white noise, the differential equations based on the energy balance were made for each equilibrium heat transfer process.

$$\frac{dT_e}{dt}=\frac{T_o-T_e}{C_eR_{w,o}}+\frac{T_{in}-T_e}{C_eR_{w,in}}+\sigma_e\frac{d\omega_1}{dt}\#(2\text{-}1)$$

$$\frac{dT_{in}}{dt}=\frac{T_e-T_{in}}{C_{in}R_{w,in}}+\frac{T_{fl}-T_{in}}{C_{in}R_{fl,in}}+\frac{T_o-T_{in}}{C_{in}R_{win}}+\sigma_{in}\frac{d\omega_2}{dt}\#(2\text{-}2)$$

$$\frac{dT_{fl}}{dt}=\frac{T_{in}-T_{fl}}{C_{fl}R_{fl,in}}+\frac{T_{pp}-T_{fl}}{C_{fl}R_{pp,fl}}+\frac{A_wfP_s}{C_{fl}}+\sigma_{fl}\frac{d\omega_3}{dt}\#(2\text{-}3)$$

$$\frac{dT_{pp}}{dt}=\frac{T_{fl}-T_{pp}}{C_{pp}R_{pp,fl}}+\frac{T_b-T_{pp}}{C_{pp}R_{pp,out}}+\frac{Q_{heating}}{C_{pp}}+\sigma_{pp}\frac{d\omega_4}{dt}\#(2\text{-}4)$$

Where T_e represents the temperature of the building envelope; T_o represents the outdoor air temperature; T_{in} represents the indoor air temperature; T_{fl} represents the temperature of the upper surface of the heated floor; T_{pp} is the temperature of the collector node assuming the entire duct plane; T_b is the soil temperature; C_e represents the specific heat capacity of the exterior wall; C_{in} represents the specific heat capacity of the indoor air; C_{fl} represents the specific heat capacity of the floor; C_{pp} is the specific heat capacity of the entire duct; $R_{w,o}$ represents the thermal resistance between the outdoor air and the building envelope; $R_{w,in}$ represents the building thermal resistance between the envelope and the indoor air; $R_{fl,in}$ represents the thermal resistance

https://doi.org/10.26868/25222708.2023.1343

between the indoor air and the floor; $R_{pp,fl}$ represents the thermal resistance between the pipe and the inner surface of the floor; $R_{pp,out}$ represents the thermal resistance between the lower surface of the pipe and the soil; A_w represents the area of the external windows; P_s represents the solar radiation; f represents the effective conversion coefficient of the solar radiation; $Q_{heating}$ is the heat supply of the TABS system; $\sigma_i \frac{d\omega_i}{dt}$ represents the noise of different process; RC of each node are the parameters to be identified.

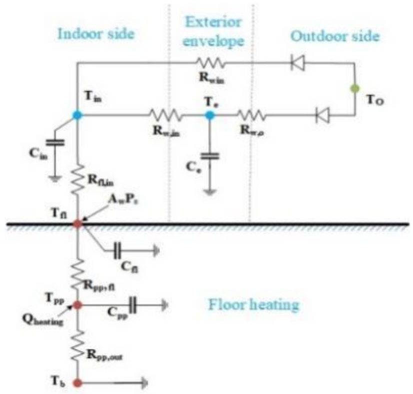

Figure 2-3 Grey box model of the case TABS system

Modelica model of the case study

In order to test the performances of different control strategies, a Modelica model of the case study was established and validated by the measurements. The layout of the model is shown in Figure 2-4(a), which includes mainly four aspects: outdoor weather, room model, ventilation loss and heat gain from indoor personnel and equipment. The TABS slab and the indoor air are connect through the room heat port (Heat_port). The room model uses the MixedAir model in the Buildings library, which is composed by the exterior walls, the exterior windows, the interior walls, the floor and the indoor air, as shown in Figure 2-4(b). According to the Indoor Air Quality Standard, the fresh air volume of indoor air is set to more than 30 (m^3/(h-people))[5]. As shown in Figure 3-1(a), the weather data of the typical meteorological year in Tianjin were used for the dynamic simulation[6], and the coldest two weeks of the year from February 1 to February 14 were chosen on purpose for the simulation.

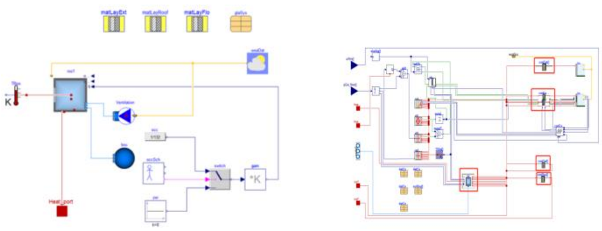

Figure 2-4 (a)Building model (b)Room model

EMPC scheme

The optimization problem of the economic model predictive control (EMPC) for radiant floor heating system is expressed as equations (2-15)-(2-21).

$$\min_{u_1,u_2\cdots u_k} \sum_{i=1}^{N_p-1} (u_k/COP)\cdot\Delta t\cdot P_k+\rho v_k \#(2\text{-}15)$$

Subject to:

$$x_{k+1}=A_d x_k+B_d u_k+E_d d_k \#(2\text{-}16)$$

$$y_k=C_d x_k+v_k \#(2\text{-}17)$$

$$z_k^{min}-v_k\le y_k\le z_k^{max}+v_k \#(2\text{-}18)$$

$$u_{min}\le u_k\le u_{max} \#(2\text{-}19)$$

$$\Delta u_{min}\le \Delta u_k\le \Delta u_{max} \#(2\text{-}20)$$

$$v_k\ge 0 \#(2\text{-}21)$$

where Np is the prediction horizon; Δt is the prediction interval; P_k is the electricity price at time k; x_k,y_k, $d_k$are the state vector, output vector and perturbation vector, respectively. v_k is the relaxation variable; $\rho$is the penalty factor. A_d,B_d,C_d,D_d are the state space matrices of the discrete-time state space model; u_k is the amount of heat added by the input water to the pipe plane at time k; u_{min} is the minimum heating power, 0; u_{max} is the maximum heating power of the heat pump heating power, kW; Δu_k is the heating power variation; Δu_{min} is the minimum heating power variation; Δu_{max} is the maximum heating power variation; COP is the performance coefficient of the heat pump, and this paper refers to the typical COP constant value, i.e., 3, for the case study[7].

If the ideal heat supply offered is 0 kW within the limitations and no heat is injected into the system, equation (2-15) is to minimize operating costs throughout the predicted period. Equations (2-16) and (2-17) provide a spatial equation of state description of the dynamics of the system. Equation (2–18) serves as a constraint to maintain the indoor air temperature within the set temperature range so that it swings between the top and lower limits of the thermal comfort temperature to satisfy the needs of the human body. To guarantee that the heating process of the system corresponds to practical situations, equations (2-19) and (2-20) place restrictions on the heat pump heating power and the amount of heating power fluctuation.

The authors included a relaxation variable (equation (2-21)) and multiplied the relaxation variable by a penalty factor big enough to fulfill the indoor temperature requirement as much as feasible to guarantee that the optimization issue is effectively addressed. With a soft restriction and state feedback, Zheng. A. et al. demonstrated that any stable system may be asymptotically stabilized[8]. The existence of a workable optimal solution is therefore guaranteed during the optimization process, and in this paper, linear programming is used to solve the optimal variable values. Soft constraints are therefore achieved by adding a penalty factor to penalize the violation of constraints in order to obtain better control performance.

The initial state at the beginning of the measurements is utilized as the starting point for optimization at the beginning of each optimization process, and $x=[T_e \quad T_{in} \quad T_{fl} \quad T_{pp}]^T$ are used as the state variables.

https://doi.org/10.26868/25222708.2023.1343

Figure 2-4 illustrates the use of Kalman filtering to eliminate measured error and recover the original data and generate the iterative input.

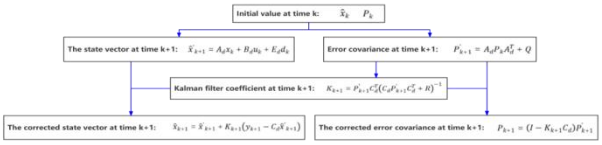

Figure 2-4 Kalman filtering cycle flow chart

Results

System model identification

With a forecast period of N=336h and a sampling interval of Ts=1h in this paper, the EMPC strategy is employed for heating in the two coldest weeks. As a result, the control signal is output and data is collected every hour. The prediction range in the TABS system is larger and the thermal response time of the room is longer. Its prediction range is typically set to 6-48h[9]. Considering the long thermal response time of the target room , the prediction horizon in this study is chosen as Np = 8h[2], which is for optimizing the operating cost during the very period, and generating the optimal control sequence for the following hour to start executing. .

The zero-order hold approach is used to create the discrete-time state-space model matrix from the identified RC parameter values with the forecast interval Ts=1h in accordance with the weather circumstances. The input outdoor weather data is displayed in Figure 3-1(a).The identified parameter matrices A_d, B_d, E_d, and C_d are:

$$A_d = \begin{pmatrix} 0.7808 & 0.0104 & 0.1502 & 0.0400 \\ 0.5082 & 0.0140 & 0.3179 & 0.1390 \\ 0.3673 & 0.0159 & 0.4033 & 0.1909 \\ 0.2068 & 0.0147 & 0.4040 & 0.3076 \end{pmatrix};$$

$$E_d = \begin{pmatrix} 0.0166 & 0.0681 & 0.0020 \\ 0.0083 & 0.3133 & 0.0125 \\ 0.0042 & 0.4470 & 0.0184 \\ 0.0017 & 0.2414 & 0.0653 \end{pmatrix};$$

$$B_d = (0.0003 \quad 0.0046 \quad 0.0089 \quad 1.2979)^T;$$

$$C_d = (0 \quad 1 \quad 0 \quad 0).$$

EMPC performance analysis

By coupling the dynamic building model and the control strategy code, the performance of EMPC was simulated. Figure 3-1(a) shows the outdoor ambient temperature, while Figure 3-1(b) shows the resulting indoor air temperature with the EMPC controller over the 8-hour predicted range. With the actual indoor air temperature fluctuation curve (solid green-blue line) and the comfort zone (black dotted line), the controller was able to keep the indoor air temperature fluctuating within the thermal comfort temperature zones during the whole test period. The variation of the temperatures represents the charge/discharge of TABS, which corresponds to the fluctuation of the tiered electricity price. It means the heat is consumed or accumulated by TABS as much as possible during the low-price period under the EMPC regulation, while the stored heat is released to maintain the indoor temperature during the high-price period .

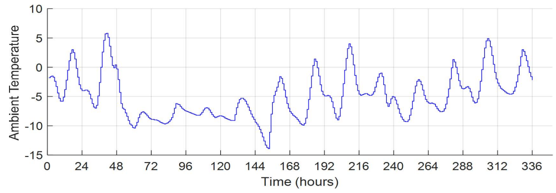

Figure 3-1(a) Outdoor ambient temperature

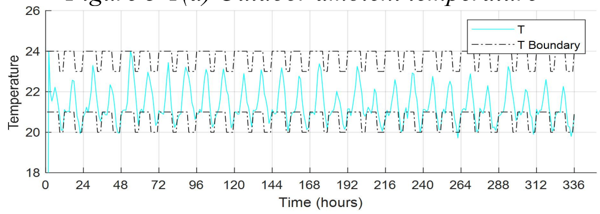

Figure 3-1(b) Room temperature using EMPC

Figure 3-2 shows the control of the electric heat pump as the heating source and the tiered electricity price. From the diagram, the operation of the heat pump occurs primarily during the low and flat periods, with sporadic occurrences at the end of the high price period. This is because the heating of the room must be initiated when the indoor air temperature drops to the lower limit of the indoor bound temperature in order to maintain the indoor heat demand. Although the heat may occasionally be required towards the end of the high price period, it is clear that the heat supply has been effectively distributed to the low and flat price period. This considerably reduces the heating intension during the peak period and decreases the overall heating expense by the proposed load shifting.

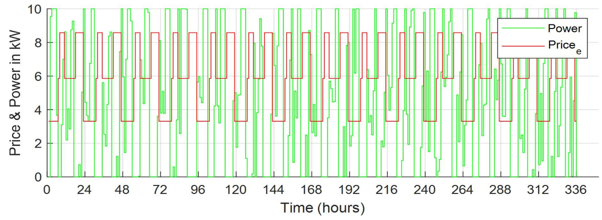

Figure 3-2 Heating power and time share tariff using EMPC

Compared with RBC

The flexibility factor (FF) was used to evaluate the ability of radiant floors to transfer thermal loads from high to low price[10]. The FF ranges from -1 to 1. FF = 1 is the best case, which means that the entire energy can be transferred to the low price period. On the contrary, the value of FF is 0, which means that the building thermal mass has limited flexibility to transfer thermal loads to the low price period. The extreme case is FF = -1, which means that all energy consumption occurs in the high price period and the system has no flexibility to transfer the thermal load.

Figure 3-3(a)-(d) show the detail of 14 days of RBC and EMPC on FF and electricity cost. EMPC has a reduced control flexibility compared to RBC. However, in order to avoid any use of high price heat, the RBC control

https://doi.org/10.26868/25222708.2023.1343

strategy has to store the heat during the low-price period as much as possible, thus more energy is consumed to compensate the extra heat loss due to the more-than-necessary thermal storage in the building thermal mass. In contrast, EMPC helps to achieve the load shifting while concerning the operation cost. So although RBC control has higher FF value, its energy price cost is much higher than EMPC.

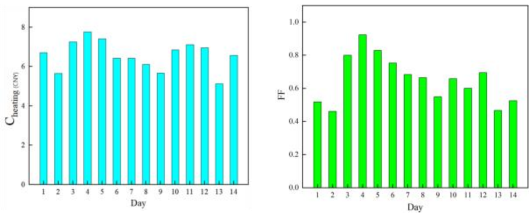

Figure 3-3(a) Electricity cost with EMPC   Figure 3-3(b) Flexibility factor with EMPC

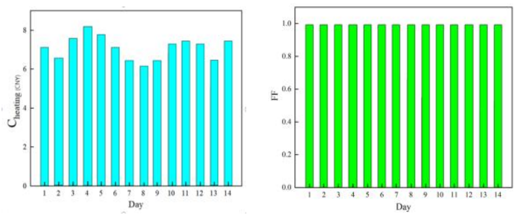

Figure 3-3(c) Electricity cost with RBC   Figure 3-3(d) Flexibility factor with RBC

Conclusions

In this study, we apply the EMPC approach to the TABS system while taking into account the effects of the soil temperature, the occupancy rate, and the dynamic power price. To predict the thermodynamic variation of the building using the TABS system, a gray-box prediction model represented by stochastic state-space equations is developed. White noise is used to make the simulated situation more realistic, and Kalman filtering is used to perform feedback correction to correct the model prediction bias and restore the real data. The room heating is then continuously optimized while a mixed integer linear programming problem is formed with the economic cost as the goal function.

The experimental results demonstrate that the EMPC controller of the TABS system can achieve automatic optimal heating and can transfer demand loads from high price to low price periods without violating human thermal comfort, i.e., the room temperature fluctuation is within the range of human thermal comfort temperature, effectively reducing or avoiding energy consumption in the peak period. EMPC also works well in terms of thermal comfort, keeping the room's temperature precisely controlled and preventing daytime overheating.Additionally, the EMPC controller's adjustable thermal load might help the grid operator economically. Comparing to RBC,EMPC has better economic benefits.

Reference

[1] I.I.O.F. Standardization, ISO 7730. Ergonomics of the Thermal Environment﹣Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the Pmv and Ppd Indices and Local Thermal Comfort Criteria, Management 52 (2005).

[2] M. Hu, F. Xiao, J.B. Jørgensen, R. Li, Price-responsive model predictive control of floor heating systems for demand response using building thermal mass, Appl Therm Eng 153 (2019) 316-329.

[3] M. Casini, Chapter 10 - Building automation systems, Construction 4.0, Woodhead Publishing2022. pp. 525-581.

[4] MHURD, AQSIQ, Design Code for Heating Ventilation and Air Conditioning of Civil Buildings, GB50736-2012, 2012.

[5] G.B. T, Indoor air quality standard, Ministry of Environmental Protection of the People’s Republic of China ⋯, 2002.

[6]EnergyPlus. https://energyplus.net/weather.November 27, 2022).

[7] R. Halvgaard, N.K. Poulsen, H. Madsen, J.B. Jørgensen, Economic model predictive control for building climate control in a smart grid, 2012 IEEE PES innovative smart grid technologies (ISGT), IEEE, 2012, pp. 1-6.

[8] A. Zhang, M. Morari, Stability of model predictive control with soft constraints, Proceedings of 1994 33rd IEEE Conference on Decision and Control, IEEE, 1994, pp. 1018-1023.

[9] M. Killian, M. Kozek, Ten questions concerning model predictive control for energy efficient buildings, Build Environ 105 (2016) 403-412.

[10] X. Yang, L. Pan, W. Guan, H. Ma, C. Zhang, Heat flexibility evaluation and multi-objective optimized control of a low-energy building with district heating, Energ Buildings 277 (2022) 112523.

https://doi.org/10.26868/25222708.2023.1343