Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 9 (2023) 227–235
www.elsevier.com/locate/egyr

2022 3rd International Conference on Power, Energy and Electrical Engineering (PEEE 2022)
18–20 November 2022

Demand response with active phase change material based thermal energy storage in buildings

Aneesh Chandra Nunna[a,b], Yi Zong[a,*], Laurent Georges[b], Shi You[a]

[a] *Department of Wind and Energy Systems, Technical University of Denmark, Roskilde 4000, Denmark*
[b] *Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim 7044, Norway*

Received 17 December 2022; accepted 27 December 2022
Available online xxxx

Abstract

A large potential to shift the electricity consumption to adapt to the stochastic renewable electricity generation is identified through the utilisation of a combination of Heat Pumps (HP) and local Thermal Energy Storage (TES) devices in building heating systems. In this paper, a building heating system coupled with an active Phase Change Material (PCM) TES device and a HP is simulated to characterise its potential for Demand Response (DR) applications. A control-oriented numerical model for the PCM TES is developed and previously validated numerical models of the building, HP and hot water radiators are integrated to simulate the dynamics of the coupled building heating system. A Genetic Algorithm (GA) based control strategy is designed to optimise the building heating energy consumption and operational cost with respect to time-varying electricity price signals. The developed control strategy is successfully implemented to utilise the TES capability of the PCM and the thermal inertia of the building to intelligently shift the electrical load of the HP to low price periods, while satisfying the specified indoor comfort requirements. In comparison to a reference case utilising a sensible TES, cost savings and consumption reductions of more than 40% and 30%, respectively, are attained with the active PCM TES. Simulation results indicate that utilising an active PCM TES over a sensible TES offers significant advantages for DR applications in building heating systems in terms of load shift flexibility, energy costs and consumption.

Peer-review under responsibility of the scientific committee of the 3rd International Conference on Power, Energy and Electrical Engineering (PEEE 2022).

Keywords: Active Phase Change Material; Demand Response; Genetic Algorithm; Thermal Energy Storage; Power to Heat

1. Introduction

The share of variable Renewable Energy Sources (VRES), such as wind and solar energy, in the power grid is continuously increasing as part of the global energy transition towards sustainable energy sources. Integrating these intermittent and fluctuating VRES requires generating additional flexibility in the power system, as the VRES are not necessarily correlated with electricity demand. The coupling of the power and heat sectors is a promising

* Corresponding author.
E-mail address: yizo@dtu.dk (Y. Zong).

https://doi.org/10.1016/j.egyr.2022.12.131

Peer-review under responsibility of the scientific committee of the 3rd International Conference on Power, Energy and Electrical Engineering (PEEE 2022).

Nomenclature

Acronyms

DR	Demand Response
GA	Genetic Algorithm
HP	Heat Pump
HTF	Heat Transfer Fluid
MPC	Model Predictive Control
PCM	Phase Change Material
PFH3	Power FlexHouse 3
TES	Thermal Energy Storage

Symbols

$\boldsymbol{J}$	Objective function
$\boldsymbol{u}$	Control input vector
$\boldsymbol{v}$	Information vector
$\boldsymbol{x}$	State vector
$\dot{m}$	Mass flow rate (kg s^{-1})
$\dot{Q}$	Heat flow rate (W)
Φ	Thermal power (W)
Φ_s	Solar irradiation (W m^{-2})
C	Electricity price
c_p	Specific heat capacity of water (kJ kg^{-1} K^{-1})
T	Temperature (°C)
T_p	Prediction horizon
U	Thermal transmittance (W m^{-2} K^{-1})
X	Liquid fraction

Subscripts

b	Basement
e	Envelope
f	Floor

avenue for improving the degree of grid flexibility [1]. Further, flexible usage of electricity to satisfy heating demand through a combination of Thermal Energy Storages (TES) and Demand Response (DR) solutions contributes to the decarbonising of the heating sector [2].

A key pillar in the European energy policy, which aims to achieve climate neutrality in Europe by 2050, is the built environment. The building sector alone is responsible for more than 40% of the total final energy in Europe, of which space heating accounts for approximately 60%. Therefore, buildings have been identified as a significant source for DR due to their high thermal inertia and huge energetic impact [3]. DR of a building entails the ability to intelligently control the electricity demand of the building based on power grid incentives. Electrical Power-to-Heat (P2H) devices, such as a Heat Pump (HP), combined with TES are identified as the most mature and effective technology for shifting peak loads and reducing energy costs to achieve DR in buildings [4]. TES devices facilitate the capture and storage of energy during periods of low demand (off-peak hours) and provide energy during high demand periods (peak hours).

Phase Change Material (PCM) TES systems store energy in the latent heat of a PCM by altering its phase within a narrow temperature range. Relative to sensible storage materials, PCMs have high energy storage density, recovery of thermal energy occurs at almost constant temperature and have the ability to store a large amount of energy when the temperature difference between the heat source and the sink is low. These properties make them ideal for building heating applications. Active PCM TES systems involve the integration of smart control techniques that enable the system to absorb, store and release energy on demand, resulting in more efficient heat transfer and less energy consumption [5].

In literature, various control strategies have been employed to identify the maximum flexibility provided by a building system. A numerical study is presented in [6] to quantify the demand flexibility of PCM TES integrated with a building heating system and concluded that PCM TES can be designed to provide short-term flexibility. A review of TES for DR applications in buildings [7] found that by far the most common TES investigated has been sensible TES with water as the energy store. The few research studies that have implemented control strategies for active PCM TES systems mainly find application in solar thermal building systems. In [8] a Model Predictive Control (MPC) strategy was developed to control the heating process for a standard building equipped with a heat exchanger unit, containing a PCM, which is thermally charged by solar energy and results indicate that cost savings of about 20%–40% are possible. A Genetic Algorithm (GA) was employed by [9] to optimise the building envelope temperature to minimise the cooling demand for an office building enhanced with passive PCM.

In this study, a GA based control strategy is developed for a residential building heating system equipped with a HP, hot water radiators and coupled with a PCM TES device. A control-oriented numerical model of the actively charged and discharged PCM TES is developed. Further, models of the building heating system, HP and hot water radiators from literature are utilised to form an integrated numerical model of the coupled system dynamics. Simulations show that active PCM TES integrated with the building heating system can generate increased load-shift flexibility on the demand side while also reducing end user energy costs when compared against a sensible TES for the same building [10,11]. In fact, the operational energy costs and consumption are shown to be reduced by more than 30% while satisfying the building space heating demand and indoor comfort requirements.

The objective of this study is to characterise the potential of DR of an active PCM TES coupled building heating system. This study aims to demonstrate the advantages offered by a PCM TES over a sensible TES in terms of increased load shift flexibility and reduction in operational energy costs. This work contributes to new knowledge on how intelligent control strategies can be implemented to maximise the benefits of integrating active PCM TES for DR in smart residential buildings.

2. The building heating system

PowerFlexHouse3 (PFH3), shown in Fig. 1(a), is a 150 m^2 three-storied intelligent residential building located at DTU Risø. The heating system is comprised by a set of hot water radiators with controllable inlet electro valves for flow rate control, an air-source electric driven HP and an active PCM TES. A continuous time nonlinear grey-box model of the building, formulated as a set of nonlinear Stochastic Differential Equations (SDE), to simulate the building thermodynamics is adopted from [12]. It consists of a set of SDEs, shown in Eq. (1), developed based on prior physical knowledge of the system and real-time data, that describe the various thermal flows in the building (Fig. 1(b)). The validated parameters of the model are listed in Table II of [12]. The heat exchange is modelled as a Resistor–Capacitor equivalent circuit representing the building indoor and envelope temperatures, windows, and ambient temperature with the following assumptions:

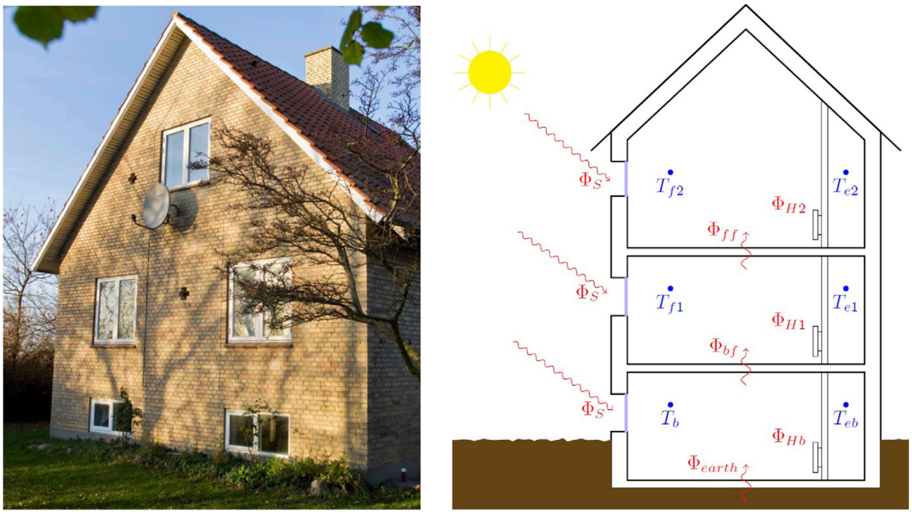
1. Indoor and envelope temperatures (T_i, T_{ei}) are considered homogeneous in each state.
2. Hot water radiators are modelled as resistance heaters and act as sources of direct heat input.
3. Solar irradiation (Φ_s) incident on the main windows is the only significant source of radiative heat transfer.
4. Each floor is considered as a single room where all the radiators are grouped as one input for each floor.

$$C_b \frac{\mathrm{d}T_b}{\mathrm{d}t} = \frac{T_{f1} - T_b}{R_{fb}} + \frac{T_{eb} - T_b}{R_{eb}} + u_b \Phi_b^{\max} + A_{wb} \Phi_s + \sigma_b \frac{\mathrm{d}\omega_b}{\mathrm{d}t} \tag{1a}$$

$$C_{eb} \frac{\mathrm{d}T_{eb}}{\mathrm{d}t} = \frac{T_{\mathrm{earth}} - T_{eb}}{R_{eeb}} + \frac{T_b - T_{eb}}{R_{beb}} + \sigma_{eb} \frac{\mathrm{d}\omega_{eb}}{\mathrm{d}t} \tag{1b}$$

$$C_{f1} \frac{\mathrm{d}T_{f1}}{\mathrm{d}t} = \frac{T_{f2} - T_{f1}}{R_{ff}} + \frac{T_b - T_{f1}}{R_{fb}} + \frac{T_{e1} - T_{f1}}{R_{f1e1}} + u_1 \Phi_{f1}^{\max} + A_{w1} \Phi_s + \sigma_{f1} \frac{\mathrm{d}\omega_{f1}}{\mathrm{d}t} \tag{1c}$$

$$C_{e1} \frac{\mathrm{d}T_{e1}}{\mathrm{d}t} = \frac{T_a - T_{e1}}{R_{e1a}} + \frac{T_{f1} - T_{e1}}{R_{f1e1}} + \sigma_{e1} \frac{\mathrm{d}\omega_{e1}}{\mathrm{d}t} \tag{1d}$$



(a) (b)

Fig. 1. (a) PFH3 building. (b) Building temperature states and thermal flows.

$$C_{f2}\frac{\mathrm{d}T_{f2}}{\mathrm{d}t} = \frac{T_{f1}-T_{f2}}{R_{ff}} + \frac{T_{e2}-T_{f2}}{R_{f2e2}} + u_2\Phi_{f2}^{\max} + A_{w2}\Phi_s + \sigma_{f2}\frac{\mathrm{d}\omega_{f2}}{\mathrm{d}t} \tag{1e}$$

$$C_{e2}\frac{\mathrm{d}T_{e2}}{\mathrm{d}t} = \frac{T_a-T_{e2}}{R_{e2a}} + \frac{T_{f2}-T_{e2}}{R_{f2e2}} + \sigma_{e2}\frac{\mathrm{d}\omega_{e2}}{\mathrm{d}t} \tag{1f}$$

2.1. PCM TES

The PCM TES is a tube-in-tank type system comprising of a cylindrical tank filled with PCM and a central tube circulating with water as the Heat Transfer Fluid (HTF). During charge, the PCM melts as heat is injected from the HP and stored as latent heat. During discharge, the PCM solidifies and the stored heat is released to the building via the hot water radiators. A schematic description of the tank is shown in Fig. 2. An organic PCM, 1-octadecanol, is chosen as the PCM due its high latent heat and energy storage density, good chemical and thermal stability, low cost, and non-toxic nature, which makes it attractive for domestic applications [13]. A numerical model of the tank is developed based on the effectiveness-Number of Transfer Units ($\epsilon - NTU$) method [14]. The model sufficiently captures the dynamic behaviour and is an effective numerical tool for control-oriented optimisation and simulation purposes. The developed model includes both sensible heat and latent heat stored in the PCM and is based on the following assumptions [15]:

1. Inlet temperature and velocity of the HTF are constant and the outer walls of tank are adiabatic.
2. The model is axisymmetric and the thermophysical properties are assumed to be constant.
3. Natural convection in the liquid phase of the PCM is ignored.

Energy equations are formulated to model the phase change process by dividing the tank into small control volumes (index i, length Δl). Relations in Eq. (2) are used to obtain the convective heat transfer coefficient (h), number of thermal units (NTU), HTF temperature (T_{HTF}) and heat transfer rate ($\dot{Q}$) respectively. The formulated energy equations are then solved, depending on the phase of the PCM, for each control volume to obtain the temperature of the PCM (T_{PCM}) when in sensible heat or the liquid fraction (X_{PCM}) during melting/solidification process. The thermophysical values of the PCM and HTF along with the geometrical parameters of the cylindrical tank are listed in Table 1.

$$h = \frac{Nu \cdot k_{PCM}}{2 \cdot R_i} \tag{2a}$$

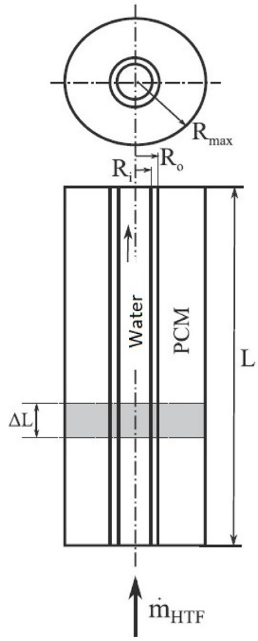


Fig. 2. PCM TES schematic.

Table 1. PCM and HTF thermophysical values along with tank geometrical parameters.

Description	Parameter	Value	Unit
Dynamic viscosity of HTF	μ_{HTF}	0.55	$m^2\,s^{-1}$
Latent heat of melting of PCM	L_{PCM}	269.3	$kJ\,kg^{-1}$
Conduction heat transfer coefficient of PCM	k_{PCM}	160	$kW\,K^{-1}\,m^{-1}$
Melting temperature of PCM	T^m_{PCM}	55	°C
Specific heat of PCM	c_{PCM}	2.178	$kJ\,kg^{-1}\,K^{-1}$
Mass of PCM	m_{PCM}	110	kg
Tube inner radius	R_i	0.0127	m
Tube outer radius	R_o	0.0132	m
Tank radius	$R_{\max}$	0.04	m
Height of tank	l	2	m

$$\frac{1}{UA} = \begin{cases} \dfrac{1}{h2\pi R_i \Delta l} + \dfrac{\ln\left({}^{R_o}/_{R_i}\right)}{2\pi k \Delta l} & : \text{Sensible} \\ \dfrac{1}{h2\pi R_i \Delta l} + \dfrac{\ln\left({}^{R_o}/_{R_i}\right)}{2\pi k \Delta l} + \dfrac{\ln\left({}^{R}/_{R_i}\right)}{2\pi k_{PCM} \Delta l} & : \text{Latent} \end{cases} \tag{2b}$$

$$NTU = \frac{UA}{\dot{m}_{HTF} \cdot c_{HTF}} \tag{2c}$$

$${}^{i+1}_{t}T_{HTF} = \frac{2 \cdot NTU \cdot {}^{i}_{t}T_{PCM} + (2 - NTU) \cdot {}^{i}_{t}T_{HTF}}{2 + NTU} \tag{2d}$$

$${}^{i}_{t}\dot{Q} = \dot{m}_{HTF} \cdot c_{HTF} \cdot \left({}^{i+1}_{t}T_{HTF} - {}^{i}_{t}T_{HTF}\right) \tag{2e}$$

$$\text{Mode} = \begin{cases} \text{Sensible:} \quad {}^{i}_{t+1}T_{PCM} = {}^{i}_{t}T_{PCM} - \dfrac{{}^{i}_{t}\dot{Q} \cdot \Delta t}{m_{PCM} \cdot c_{PCM}} \\ \text{Latent:} \quad {}^{i}_{t+1}X_{PCM} = {}^{i}_{t}X_{PCM} - \dfrac{{}^{i}_{t}\dot{Q} \cdot \Delta t}{m_{PCM} \cdot L_{PCM}} \end{cases} \tag{2f}$$

Table 2. Radiator thermal capacity (kW).

Floor	Maximum	Nominal
Basement	2.208	4.343
Floor 1	5.002	9.860
Floor 2	1.791	3.528

2.2. Heat pump

The HP is an electric driven air-source HP with a thermal capacity of 15 kW and an electric consumption of 3 kW. By being connected to the PCM TES, it decouples the energy supply from demand, thereby providing an opportunity to shift the electrical load intelligently. For optimisation purposes, a control-oriented linear model is utilised wherein the COP (Coefficient of Performance) of the HP is dependent on the air source temperature (T_a), as shown in Eq. (3a). The condenser mass flow rate ($\dot{m}_{con}$) is obtained through Eq. (3b) as a function of the binary input control variable (u_{HP}) which determines the ON/OFF status. The condenser outlet temperature setpoint is set to be 65 °C.

$$COP = COP_0 + a_1 T_a \tag{3a}$$

$$\dot{m}_{con} = \frac{u_{HP} \cdot P_{HP}^{\max} \cdot COP}{c_p \cdot \left(T_{con}^{out} - T_{con}^{in}\right)} \tag{3b}$$

2.3. Hot water radiator

Typical two-pipe hot water radiators, with a supply and return line, are installed in each floor of the building to maintain the indoor thermal comfort. The heat source for the radiators is the PCM TES. The nominal temperature spread of the radiator is taken to be $\Delta T_{nom} = 50\,°\mathrm{C}$. Table 2 lists the maximum power and the nominal power (calculated for a nominal flow temperature of 65 °C) of the radiators on each floor. In Eq. (4a), the building heat demand ($\dot{Q}_{PFH3}$) is derived as a function of the radiator control input (u_i). The mass flow rate ($\dot{m}_{rad}$) and the return temperature (T_{ret}) from the radiators are calculated as a function of the building heat demand ($\dot{Q}_{PFH3}$) through Eqs. (4b) and (4c).

$$\dot{Q}_{PFH3} = u_b \Phi_b^{\max} + u_1 \Phi_{f1}^{\max} + u_2 \Phi_{f2}^{\max} \tag{4a}$$

$$\dot{m}_{rad} = \frac{\dot{Q}_{PFH3}}{2 \cdot c_p \cdot \left[T_{flow} - \left(\frac{\dot{Q}_{PFH3}}{\dot{Q}_{nom}}\right)^{1/n} \cdot \Delta T_{nom} - T_{ind}\right]} \tag{4b}$$

$$T_{ret} = 2 \cdot \left[\Delta T_{nom} \cdot \left(\frac{\dot{Q}_{PFH3}}{\dot{Q}_{nom}}\right)^{1/n} + T_{ind}\right] - T_{flow} \tag{4c}$$

3. Control strategy

The dynamics of the integrated building heating system, shown schematically in Fig. 3(a), are stochastic, highly non-linear, discontinuous and non-differentiable, and where the control variables take discrete and binary values. GA is a powerful stochastic population based algorithm that can address this type of mixed integer nonlinear optimisation problem [16]. GA repeatedly modifies a population of individual solutions at each step by selecting individuals at random from the current population to be parents and uses them to produce the children for the next generation. Iterating over successive generations, the population evolves toward an optimal solution by producing candidate solutions with higher fitness values than the previous generation. In literature, GA is considered a robust heuristic approach for optimisation problems in the field of building performance [17]. Thus, based on the GA framework described in [18], an intelligent control strategy is designed to schedule the HP to optimally utilise the energy storage capability of the PCM TES to shift the electrical load to low electricity price periods while ensuring that

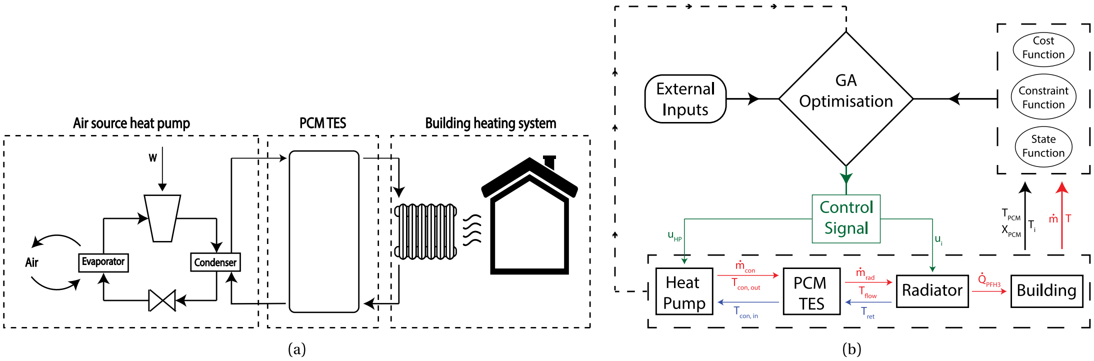


Fig. 3. (a) Integrated building heating system scheme. (b) Functional block diagram of the control strategy.

Table 3. Comparison between active PCM TES and sensible TES.

Energy	Sensible TES [10]	Active PCM TES	Savings (%)
cost (€)	5.19	3.01	42%
consumption (kW h)	150.04	103.52	31%

the building indoor temperature is kept within the desired comfort requirements. A functional block diagram of the developed strategy is shown in Fig. 3(b).

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{v}(t)) \tag{5a}$$

$$\boldsymbol{J} = \sum_{t}^{t+T_p} C(t) \cdot u_{HP}(t) \tag{5b}$$

$$\text{Indoor comfort constraint} = \begin{cases} \text{Day time:} & 21 \leq T_i(t) \leq 23 \\ \text{Night time:} & 20 \leq T_i(t) \leq 22 \end{cases} \tag{5c}$$

$$\sum_i \left[m_{PCM} \cdot c_{PCM} \cdot \left({}^i_t T_{PCM} - T_{ref} \right) + m_{PCM} \cdot {}^i_t X_{PCM} \cdot L_{PCM} \right] \geq \dot{Q}_{PFH3}(t) \cdot T_s \quad : \forall t \in T_p \tag{5d}$$

The developed numerical models of the building heating system, PCM TES, HP and hot water radiator are integrated into the state function $\boldsymbol{f}$ in Eq. (5a) to represent the dynamics of the integrated system. The state vector $\boldsymbol{x}$ contains information regarding both the building temperature states (T_i, T_{ei}) and the PCM TES states (${}^i_t T_{PCM}$, ${}^i_t X_{PCM}$). The binary control input variable $\boldsymbol{u} = [u_{Rb}\ u_{R1}\ u_{R2}\ u_{HP}]$ determines the radiators valve open/close position and the HP ON/OFF status. The information vector $\boldsymbol{v} = [T_a\ \Phi_s\ C]$ contains information about the weather, the ambient temperature and solar irradiation level obtained from the local Risøweather station, and the hourly day-ahead electricity price C obtained from [19]. The objective function $\boldsymbol{J}$ in Eq. (5b) is designed to find the most economical moments for driving the electric load. In Eq. (5c), constraints are placed on the building indoor states to ensure that they remain within the indoor comfort boundary 21 °C to 23 °C, as defined by ISO-7730 for regular buildings during winter. The comfort boundary is lowered by 1 °C during night-time (19:00 to 07:00). Constraint in Eq. (5d) ensures that there is sufficient energy stored in the PCM to satisfy the building heating demand over the prediction horizon T_p.

As an illustrative example, the integrated system is simulated over a period of 10 days with a sampling interval $T_s = 1$ h, and the results are displayed in Fig. 4. The charging schedule of the developed control strategy is compared with a reference case, where a sensible TES was controlled using an MPC strategy [10]. It is observed that the developed GA strategy intelligently shifts the HP electric consumption to low price periods while simultaneously ensuring that the building indoor temperatures are maintained within the desired comfort zone. Crucially, the charging schedule of the PCM TES is optimised in a such a way that it does not coincide with the building heat load, thus successfully demonstrating its potential for DR applications. By shifting the consumption smartly, increased energy cost savings and reduced energy consumption are observed, and the results are listed in Table 3. Thus, the

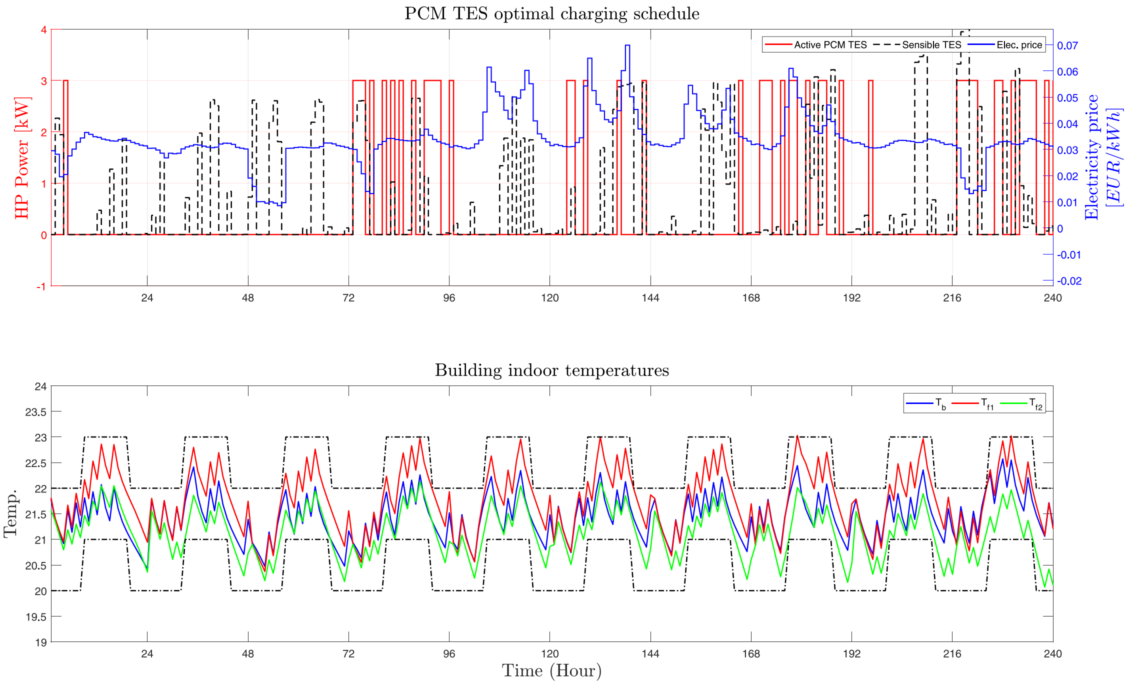


Fig. 4. Simulation results showing the DR capability of the integrated building heating system.

Table 4. GA parameters.

Parameter	Value
Population size	100
Maximum generations	100
Maximum stall generations	15
Elite count fraction	0.05
Crossover fraction	0.8
Constraint tolerance	10^{-3}
Function tolerance	10^{-6}

objective to reduce end-user energy costs is achieved and savings of more than 40% are demonstrated. In Table 4, the parameters of the GA solver are listed. The computational performance of the developed strategy varies with the day, sampling interval and the GA parameters, but on average it takes less than 3 min to compute a 24-hour optimal charging schedule when tested on a 11th Gen Intel(R) Core(TM) i5-1145G7 @ 2.60 GHz 2.61 GHz 16 GB RAM computer running MATLAB R2022a.

4. Conclusion

In this study, the design and development of an intelligent control strategy, based on GA, is presented for a building heating system coupled with an active PCM TES. Control oriented numerical models for the PCM TES are developed and previously validated models of the building heating system, HP and hot water radiator are integrated to simulate the coupled system dynamics. The developed control strategy intelligently utilises the TES capability of the system to shift the electricity demand of the HP based on electricity price signals. Results show the capability of the developed control to optimally schedule the charging the PCM TES to achieve the dual objective of shifting electrical load to low price periods and reduce energy costs, while ensuring that the building indoor comfort requirements are satisfied. In comparison to a reference case using sensible TES, the developed GA strategy achieved operational energy cost savings of 42% and reduction in energy consumption by 31%. In conclusion, this study demonstrates that PCM TES can provide a significant opportunity for increased load-shift flexibility and can be a powerful tool in the domain of P2H solutions for achieving DR in building heating systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgements

This work is supported by the EU Horizon 2020 project “Compact bio-based thermal energy storage for buildings” (ComBioTES) (No. 864496). The author, Aneesh Chandra Nunna, is supported by the Technical University of Denmark through the Alliance PhD scholarship.

References

[1] Jimenez-Navarro J-P, Kavvadias K, Filippidou F, Pavičević M, Quoilin S. Coupling the heating and power sectors: The role of centralised combined heat and power plants and district heat in a European decarbonised power system. Appl Energy 2020;270:115134. http://dx.doi.org/10.1016/j.apenergy.2020.115134.

[2] Bloess A, Schill W-P, Zerrahn A. Power-to-heat for renewable energy integration: A review of technologies, modeling approaches, and flexibility potentials. Appl Energy 2018;212:1611–26. http://dx.doi.org/10.1016/j.apenergy.2017.12.073.

[3] Guelpa E, Verda V. Demand response and other demand side management techniques for district heating: A review. Energy 2021;219:119440. http://dx.doi.org/10.1016/j.energy.2020.119440.

[4] Chen Y, Xu P, Gu J, Schmidt F, Li W. Measures to improve energy demand flexibility in buildings for demand response: A review. Energy Build 2018;177:125–39. http://dx.doi.org/10.1016/j.enbuild.2018.08.003.

[5] Gholamibozanjani G, Farid M. A critical review on the control strategies applied to PCM-enhanced buildings. Energies 2021;14(7). http://dx.doi.org/10.3390/en14071929.

[6] Finck C, Li R, Kramer R, Zeiler W. Quantifying demand flexibility of power-to-heat and thermal energy storage in the control of building heating systems. Appl Energy 2018;209:409–25. http://dx.doi.org/10.1016/j.apenergy.2017.11.036.

[7] Tarragona J, Pisello AL, Fernández C, de Gracia A, Cabeza LF. Systematic review on model predictive control strategies applied to active thermal energy storage systems. Renew Sustain Energy Rev 2021;149:111385. http://dx.doi.org/10.1016/j.rser.2021.111385.

[8] Gholamibozanjani G, Tarragona J, de Gracia A, Fernández C, Cabeza LF, Farid MM. Model predictive control strategy applied to different types of building for space heating. Appl Energy 2018;231:959–71. http://dx.doi.org/10.1016/j.apenergy.2018.09.181.

[9] Konstantinidou CA, Lang W, Papadopoulos AM. Multiobjective optimization of a building envelope with the use of phase change materials (PCMs) in Mediterranean climates. Int J Energy Res 2018;42(9):3030–47. http://dx.doi.org/10.1002/er.3969, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/er.3969.

[10] Awadelrahman MAA, Zong Y, Li H, Agert C. Economic model predictive control for hot water based heating systems in smart buildings. Energy Power Eng 2017;09(04):112–9. http://dx.doi.org/10.4236/epe.2017.94b014.

[11] Zong Y, Böning GM, Santos RM, You S, Hu J, Han X. Challenges of implementing economic model predictive control strategy for buildings interacting with smart energy systems. Appl Therm Eng 2017;114:1476–86. http://dx.doi.org/10.1016/j.applthermaleng.2016.11.141.

[12] Santos RM, Zong Y, Sousa JMC, Mendonça L, Thavlov A. Nonlinear economic model predictive control strategy for active smart buildings. In: 2016 IEEE PES Innovative smart grid technologies conference Europe (ISGT-Europe). 2016, p. 1–6. http://dx.doi.org/10.1109/ISGTEurope.2016.7856245.

[13] Okogeri O, Stathopoulos VN. What about greener phase change materials? A review on biobased phase change materials for thermal energy storage applications. Int J Thermofluids 2021;10:100081. http://dx.doi.org/10.1016/j.ijft.2021.100081.

[14] Tay N, Belusko M, Bruno F. Designing a PCM storage system using the effectiveness-number of transfer units method in low energy cooling of buildings. Energy Build 2012;50:234–42. http://dx.doi.org/10.1016/j.enbuild.2012.03.041.

[15] Pirasaci T, Goswami DY. Influence of design on performance of a latent heat storage system for a direct steam generation power plant. Appl Energy 2016;162:644–52. http://dx.doi.org/10.1016/j.apenergy.2015.10.105.

[16] Katoch S, Chauhan SS, Kumar V. A review on genetic algorithm: past, present, and future. Multimedia Tools Appl 2020;80(5):8091–126. http://dx.doi.org/10.1007/s11042-020-10139-6.

[17] Costa-Carrapiço I, Raslan R, González JN. A systematic review of genetic algorithm-based multi-objective optimisation for building retrofitting strategies towards energy efficiency. Energy Build 2020;210:109690. http://dx.doi.org/10.1016/j.enbuild.2019.109690.

[18] Deep K, Singh KP, Kansal M, Mohan C. A real coded genetic algorithm for solving integer and mixed integer optimization problems. Appl Math Comput 2009;212(2):505–18. http://dx.doi.org/10.1016/j.amc.2009.02.044.

[19] Nordpool. Hourly day-ahead electricity spot price market data. 2022, https://www.nordpoolgroup.com/.