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Smart control of dynamic phase change material wall system

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Abstract

This work presents two different smart control algorithms to manage a novel phase change material system integrated into building walls and roofs. This system is able to move a phase change material layer with respect to the insulation layer inside the building component. With this ability, the system can increase solar benefits in winter and take profit from night free cooling in summer. During the heating season, the system places the phase change material facing outdoors during sunny hours to melt it, and it moves the phase change material back facing indoors to provide space heating when desired. In the cooling season, the phase change material is moved to the outer face of insulation at night time to enhance its solidification process, and it is moved back to face indoors during cooling peak hours. An appropriate control system, referring to the schedule of operation and placement of phase change material layer with respect to the insulation (when phase change material is facing outdoors or indoors) is critical to achieve savings and avoid malfunctioning of the system. In this work, we have developed and numerically compared two different control algorithms based on weather forecast data for space heating and cooling applications. Experimentation has been done under four different climate conditions: Athens, Madrid, Strasbourg, and Helsinki. One of the control algorithms, based on local search (Tabu), provided the set of activations of the dynamic system for a 24 hour period. The other algorithm is based on model predictive control with an horizon of 2.5 and 5 hours. Results proved the feasibility of the two smart control methods, as well as their capacity to improve the energy benefits of the dynamic phase change material system in days with suitable weather conditions. Moreover, the two control algorithms successfully avoided activating the system in days with non-appropriate weather conditions.

Keywords: Phase Change Material (PCM), Smart Control, Tabu search, Model Predictive Control (MPC), Dynamic system, Climatic Adaptable Building Shells (CABS)

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Nomenclature

δ	delta time [s]	H	horizon time [s]
N	horizon slot	pos	activation/deactivation variable s
$\dot{Q}$	thermal power [kW]	S_{rad}	solar radiation [W/m^2]
T_{ext}	external temperature [°C]	T_i	layer i temperature [°C]
$\hat{T}_i$	layer i predicted temperature [°C]	T_{pcm}	PCM layer temperature [°C]
T_{ppc}	PCM peak phase change temprature [°C]	T_{SP}	set point temperature [°C]

1. Introduction

Appropriate passive design of buildings, especially in their envelopes, has been identified as a key aspect to reduce the increasing space heating and cooling demands in the building sector [1]. Within this context, the use of phase change materials (PCM) in building envelopes has been extensively studied due to its high energy density within a small range of temperatures [2]. This ability allows to prevent or delay the cooling peak load to the indoor environment during summer, and to absorb part of the solar irradiation in winter. In building envelope applications, PCM stores latent heat as the ambient temperature rises to the melting point (most PCM change from a solid to a liquid state). As the temperature cools down, the PCM returns to a solid phase and releases the stored latent heat. However, the technology has not been already successfully implemented into the building sector due to strong limitations such as:

- Its application is mainly limited for passive cooling purposes [3]. The use of PCM as a passive system for heating purposes is based on the capability of the PCM to absorb solar gains coming through glazed surfaces and release them during night. This operating principle limits its benefits (quantified around 4-5% [4]), its implementation mainly to internal solar exposed surfaces (internal walls or floor), and its use to climatic regions with non-severe winter conditions (otherwise, only operative during early and late winter as well as spring and autumn seasons).

- In passive cooling applications there are strong difficulties in ensuring daily cycling. The solidification process of PCM is limited as the PCM layer is not directly exposed to outdoor night temperatures, but thermally protected by the insulating layer, which makes the technology completely useless in periods when solidification cannot be ensured. Mandilaras, Stamatiadou, Katsourinis, Zannis and Founti [5] experimentally tested the use of PCM in gypsum boards in two-storey buildings and showed that PCM was only beneficial between September and June period, as night temperatures from July to August (when cooling reduction was highly required) did not allow solidification.

- Moreover, in passive cooling applications, the peak cooling load is delayed as it is accumulated in the PCM, but that accumulated heat is mainly discharged to the indoor environment because the insulating layer limits its dissipation to outdoors.

- Passive cooling PCM technology only interferes in outdoor cooling loads transmitted by conduction, but it cannot deal with internal heating loads or solar gains from openings. In fact, this technology provides higher energy consumption for space cooling in the presence of significant internal heating loads[6; 7],

An innovative system was designed to solve the previously cited drawbacks and to convert PCM passive heating and cooling technologies into a competitive and attractive solution for the building sector [8; 9]. The proposed system relies on the ability of roofs and walls to adapt the position of their layers and hence their morphology during its operation. This ability allows the system to maximize the use of solar heat in winter and free cooling in summer. On the one hand, during winter, the system is able to place the PCM at the external surface of the insulation layer, therefore exposed to solar heat. After being melted, the PCM can be moved back to the internal face of insulation, providing space heating to the indoor environment by its solidification process. On the other hand, during summer period, the system places the PCM facing outdoors during night time to enhance the discharge of absorbed heat during peak cooling load hours. This variation of the PCM position has two benefits: first, the PCM discharges outdoors the peak cooling load, and second, it facilitates the full solidification of PCM, which is required to have the PCM charged and ready to absorb the peak cooling load of the following day.

An appropriate operation scheduling of the system is crucial to maximize the energy benefits and avoid possible malfunctioning of such dynamic system. As an example of malfunctioning, it would provide an extra heating load if PCM was placed facing outdoors during winter in a cloudy day, as it would be returned to the inner part of the building envelope even colder than before. Similarly, the activation of the system in summer nights should be avoided, unless outdoor temperatures were lower than phase change temperature. Therefore, this schedule has to take into account the climate conditions, as well as the heating and cooling demand requirements from indoors. Within this frame, the system was tested using an On-Off policy, both for winter and summer periods. This On-Off policy used a fixed operation schedule for each season, selecting an hour to place PCM facing outdoors and another to move back the PCM to face indoors. These two hours of daily activation were optimized for the whole winter or summer periods, to minimize space heating and cooling loads, respectively. Even though On-Off performances were very promising both for winter [8] and summer [9], the use of this control policy limited strongly the potential of the technology as activations could not be adapted to the different daily weather conditions. The use of smart control policies able to adapt the activations of the system to the forecast climatic conditions would be very useful to maximize the thermal benefits of such novel technology and make it attractive to the building market.

Within this frame, some authors used reinforcement learning (RL) for the control of energy systems with thermal energy storage (TES). De Gracia, Fernández, Castell, Mateu and Cabeza [10] used RL techniques to identify the best control schedule of charging and discharging processes of a ventilated facade with PCM in its air chamber. The control was developed based on weather forecast and indoor conditions of the building and provided significant benefits in specific locations. Kazmi, Mehmood, Lodeweyckx and Driesen [11] presented a methodology based on RL to optimize the production of hot water systems (with water storage vessels) for buildings in a gigawatt scale. The authors concluded that 20% energy savings were achieved for the case study of 32 Dutch houses. Similarly, Vazquez-Canteli, Kämpf and Nagy [12] developed an optimized control of a heat pump and two water storage tanks (hot and cold) using RL that supplied the heating and cooling demand of a building. The aim was to maintain the adequate comfort temperatures with the minimum energy consumption. Moreover, Ruelens, Claessens, Quaiyum, De Schutter, Babuska and Belmans [13] used RL, in particular Q-iteration approach, to optimize the operational policy of an electrical water heater (with storage tank) for residential applications that minimized the energy consumption cost. The algorithm could take actions to switch on and off the electrical heater based on several temperature sensors along the water tank. Lago, Sogancioglu, Suryanarayana, Ridder and Schutter [14] used RL to optimize the control of seasonal thermal energy storage (STES) system that buffered the uncertain energy demand of the electrical grid by buying energy in the day-ahead market. The proposed control resulted in gains of $50-70\%$ of the maximum gains given by the theoretical economic bound. Furthermore, Liu and Henze[15] studied the optimization of the control of active and passive building TES systems. The studied controller was based on a hybrid method of model predictive control (MPC) and RL. The controller could take one action over the passive and one over the active TES (charge or discharge) system.

MPC was pointed out by Afram and Janabi-Sharifi [16] as the method able to achieve a lower energy consumption, while its response showed robustness to disturbances and consistent performance under varying conditions. This energy savings potential in a heating system was assessed by Široký, Oldewurtel, Cigler and Prívara [17], implementing an MPC with weather forecasting in a building located in Prague (Czech Republic). The system achieved between 15% to 28% of energy savings after a two-months experiment. In the same research line, Oldewurtel, Parisio, Jones, Gyalistras, Gwerder, Stauch et al. [18] developed a stochastic MPC to evaluate energy savings potential of such control strategy, using weather prediction. The study was carried out at simulation level, analysing the performance of the control tool through different combinations of HVAC equipment, building type, and climates. Authors figured out that a 24-hours prediction horizon was enough to overcome all the studied cases, maintaining low errors, when comparing to optimal control with perfect information. Besides, the study concluded that MPC was able to obtain high energy savings in comparison to deterministic control strategies. Furthermore, the energy savings potential of MPC was higher if implemented together with TES. In this regard, Zhao, Lu, Yan and Wang [19] studied the behaviour of MPC in a Hong Kong building with a chilled water TES tank and PV panels. The results showed reductions of 6-22% and 23-29% in energy consumption and operating costs, respectively. Another work that took advantage of sensible TES was done by Tarragona, Fernández and de Gracia [20], studying a domestic hybrid heating system with a water TES tank. The system was composed by an air-to-water heat pump and supplied by PV panels and grid, which followed a time-of-use-tariff structure. Different prediction horizons were analysed for this system, reaching the best results for an MPC system with sensible TES at 24 hours. Additionally, the authors studied the impact of using TES and PV panels either individually or together.

Results pointed out that when coupling both technologies, the heating system managed with MPC reduced by 56% the space heating cost compared to a conventional system. A step further to improve energy savings was reached with the use of MPC to control latent TES systems. In one example, Fiorentini, Wall, Ma, Braslavsky and Cooper [21] studied the behaviour of a solar-assisted HVAC system with on-site thermal energy generation and storage, managed by an hybrid MPC. Aiming at satisfying the cooling demand in a residential building in Australia, the hybrid MPC was able to cover the cooling demand, to improve the coefficient of performance (COP) of the heat pump, and to take advantage of the forecast data to optimise the system performance. Another study with MPC and latent TES system was developed by Gholamibozanjani, Tarragona, de Gracia, Fernández, Cabeza and Farid [22]. An installation with a heat exchanger filled with PCM, a solar air collector, and a backup heater was analysed at numerical level. The occupancy schedules of the domestic, office, and service buildings were considered to perform an economic savings analysis of the aforementioned heating system. Results showed that MPC was more beneficial in the domestic schedule than in the other ones. Also, authors highlighted that the correct sizing of the PCM unit was crucial to obtain more savings.

In the frame of using smart control algorithms based on weather forecast data coupled with latent TES, this work develops and compares for the first time two different smart control algorithms to operate a dynamic PCM wall system when exposed to different climatic conditions. One of them was based on local search (Tabu search) and the other one was based on MPC. These two control algorithms made use of different horizon of forecast weather data and their performances were compared against a static policy (PCM always facing indoors), and an On-Off policy, in which the PCM was moved to face outdoors and indoors just once every day, with optimized fixed hours for the whole season. The successful implementation of smart control algorithm to manage TES system in an affordable computational time would be a crucial advance in the application of such storage systems in the field of sustainable and efficient energy systems.

2. Methodology

In this section, an overview of the dynamic PCM system, the different proposed control algorithms, and the analysed case studies are described in detail. In Subsection 2.1 the dynamic system as well as the finite volume numerical model are described. After that, in Subsection 2.2 the different developed control algorithms as well as their implementation to control the dynamic system are given. Finally, the case studies of this work are shown in Subsection 2.3.

2.1. Description of the system and numerical model

In this paper, the dynamic PCM system was implemented into the south wall with a constructive system based on two layers of bricks and a mineral wool layer as insulation. The thickness of the insulation was adapted depending on the climatic conditions under the tested technology, as detailed in Subsection 2.3. As it was previously stated, the system is able to move a PCM layer contained in half of a polymeric sheet, from one side to the other of the insulation layer as shown in Figure 1. The Boolean variable *pos* determines for each time step whether PCM is facing the indoor (*pos*=0) or outdoor environment (*pos*=1). The numerical model used to evaluate the performance of the system and to compare the different control algorithms was similar to the one developed by Izquierdo-Barrientos, Belmonte, Rodríguez-Sánchez, Molina and Almendros-Ibáñez [23] which was experimentally validated. The model was based on the finite control volume method and solved the energy equation using a fully implicit scheme. The phase change processes (both melting and solidification) were modelled using the equivalent heat capacity method [24] with a triangle shaped distribution and 4 °C to cover the whole phase change range [25]. The radiosity method was used to calculate solar and thermal radiation balance, and constant convective heat transfer coefficients were considered. In the proposed system, 5.6 kg of PCM/m^2 with an enthalpy of fusion of 200 J/g was considered. For this proposed amount of PCM, the current design suggests the use of an electrical motor (100 W) for 2 s for changing the position of the PCM layer, which means an electrical consumption of 400 J to move in and out the PCM [9]. This level of electrical energy consumption is two orders of magnitude lower than the energy savings for space heating and cooling provided by the system. Two different peak melting temperatures were used in this study (T_{ppc}: 20 °C and 23 °C) to evaluate the impact of the PCM selection in the control of the whole technology. This kind of PCM can be easily found in the market by many providers [26] [27]. More details about the model, and the thermo-physical properties of the different materials can be found in de Gracia [8].

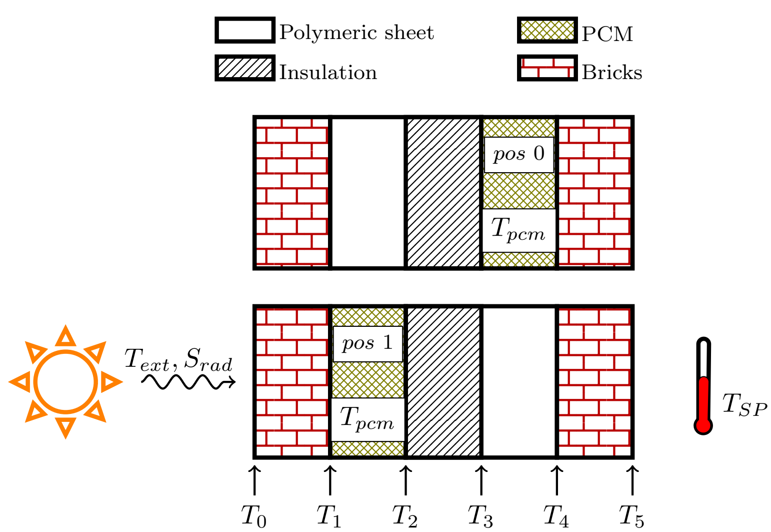

Figure 1: Schematic layout of the PCM wall system

2.2. Control algorithms description

As it was previously stated, this paper aims to develop two different control algorithms to manage the activations of the dynamic PCM wall system based on forecast weather data, and to compare its performance against another control policy without weather forecasting. In the three control policies, the operation of the system was limited to decide the PCM location with respect to the insulating layer. This section describes how each control policy was developed and implemented.

2.2.1. On-Off

A first approach to schedule the PCM wall activations was an On-Off policy. This control policy used historic weather data for each case study, and did not make use of any forecast data. Under this scenario, only two predetermined times were set: when the PCM wall was positioned facing outdoors, and when it was moved back indoors along the day. These two predetermined times were set for each season (winter and summer). As it was previously commented in the introductory Section 1, two previous studies tested the performance of the dynamic system when controlled with this algorithm both for heating and cooling applications [8; 9]. In these studies, sets of 10 days with Mediterranean climatic conditions were used to quantify the benefits of the technology against a static use of PCM in building walls.

In this paper, the On-Off time sets were optimised for the whole winter and summer seasons, separately. Moreover, in order to determine the optimal On-Off activations for each climatic conditions and case study, we performed a systematic search for the On and Off times using 30 minutes incremental slots.

2.2.2. Tabu search

The second control algorithm developed to manage the dynamic PCM wall was based on weather forecasting and local search. Local search algorithms have been proven to be effective in a wide range of combinatorial problems. Tabu search [28; 29] is one of many local search approaches that fits our purposes. Starting from a good solution, obtained by the On-Off global search mentioned before, we performed a Tabu search to obtain potential better solutions. Actually, Tabu search iteratively looks for better *neighbour* solutions, exploring their corresponding neighbourhoods to escape from local minima.

Tabu search begins, in the same way as ordinary local search, proceeding iteratively from a starting point (or solution) to another (in the neighbourhood) until a chosen termination criterion is satisfied. In our particular case, assuming $\delta = 30'$, an initial solution (S_0) is composed of 48 determined PCM positions, $S_0 = [pos_0, pos_1, \cdots pos_{47}]$ that corresponds to the day set up.

The ability of Tabu search to inspect distinct regions of the global search space is strongly linked with the definition of neighbourhood. At this point, we decided to be conservative and define, as a neighbour, any solution at a Hamming distance equal to one. That is, two solutions, S_i and S_j are neighbours if $\sum S_i \oplus S_j = 1$, where $\oplus$ is a xor operation. Then, if some of the explored neighbour solutions reduced the objective function, the process was repeated with its neighbours until the termination criterion. Of course, the objective function was the energy system performance (thermal load $\dot{Q}$), as detailed at the end of Subsection 2.2.3, for a particular day set up (or solution). In our case, the termination criterion was either no better solution was found or searching time reach a time limit (24 hours if real time operation is required).

Tabu search improved On-Off due to its ability to operate the system differently every day, and not with fixed time sets of activations, making the system able to adapt its activation depending on the weather conditions and/or the space heating and cooling demand from the building. Moreover, the use of this control algorithm allowed multiple activations per day, as the system could move the PCM either several times from one face of insulation to the other during one day, or none at all.

2.2.3. Model predictive control

The third control algorithm developed to operate the dynamic PCM system was based on MPC with weather forecasting at different horizons. MPC [30] is in essence, a control mechanism that optimises the system forecast behaviour based on its model knowledge. MPC gained momentum in late seventies in the field of industrial processes, and in recent years, it has attracted a lot of attention in the energy community, with works in different areas such as thermal control and energy consumption when applied to renewable energy sources [31].

MPC requires to define an operating time horizon (H) of the system as an optimisation problem. Usually, such problem is encoded as a Mixed Integer Non-Linear Programming (MINLP) problem [32] and requires specialised solvers to find optimal solutions such as SCIP [33]. But current state-of-the-art solvers only deal with certain type of non-linearities, making sometimes, hard or impossible to express a complex system as a quasi-linear system. This was our particular case. Our system model was based on iterative computations, being impossible to formulate it as a MINLP problem.

Consequently, in order to achieve an MPC formulation of the problem, we proceeded to obtain a linear approximation of the system model. We assumed that the system memory was limited to 2, that is, the temperature of a given layer would depend on its 2 neighbour layers at each side. Further tests with larger memory values did not show relevant improvements. Considering the layout depicted in Figure 1, the regression model resulted as:

$$
\begin{aligned}
T_{0,i+1} &= f_0(T_{ext,i}, S_{rad,i}, T_{0,i}, T_{1,i}, T_{2,i} \cdot (1-pos_i), T_{pcm,i} \cdot pos_i) \\
T_{1,i+1} &= f_1(T_{ext,i}, S_{rad,i}, T_{0,i}, T_{1,i}, T_{2,i}, T_{3,i} \cdot (1-pos_i), T_{pcm,i} \cdot pos_i) \\
T_{2,i+1} &= f_2(T_{0,i} \cdot (1-pos_i), T_{1,i}, T_{2,i}, T_{3,i}, T_{pcm,i}, T_{4,i} \cdot pos_i) \\
T_{3,i+1} &= f_3(T_{1,i} \cdot (1-pos_i), T_{2,i}, T_{3,i}, T_{pcm,i}, T_{4,i} \cdot (1-pos_i), T_{5,i} \cdot pos_i) \\
T_{4,i+1} &= f_4(T_{2,i} \cdot pos_i, T_{3,i}, T_{pcm,i}, T_{4,i}, T_{5,i}, T_{SP,i}) \\
T_{5,i+1} &= f_5(T_{pcm,i} \cdot (1-pos_i), T_{3,i} \cdot pos_i, T_{4,i}, T_{5,i}, T_{SP,i}) \\
T_{pcm,i+1} &= f_p(T_{0,i} \cdot (1-pos_i), T_{1,i} \cdot (1-pos_i), T_{pcm,i}, T_{2,i}, T_{3,i}, T_{4,i} \cdot pos_i, T_{5,i} \cdot pos_i) \\
\dot{Q}_{i+1} &= f_q(T_{4,i}, T_{5,i}) \qquad (1)
\end{aligned}
$$

being $pos_i \in [0,1]$ the PCM position at slot i, and being $f_i()\ i \in [0,5]$, $f_p()$ and $f_q()$ the linear approximations obtained from the regression model as explained below.

First, we ran up to 5 sets of numerical simulations for each city and season (50 days) with a time slot of 30', placing the PCM randomly Off (0) or On (1). Then, we implemented stochastic gradient descent [34] to obtain the regression on Eq. 1 models. Figure 2 is a 4 days example comparison of temperatures given from the validated control volume model (CVM) and the proposed linear regression model (RM) at different positions of the system (see Figure 1). As an example of the accuracy of the regression model, Table 1 shows

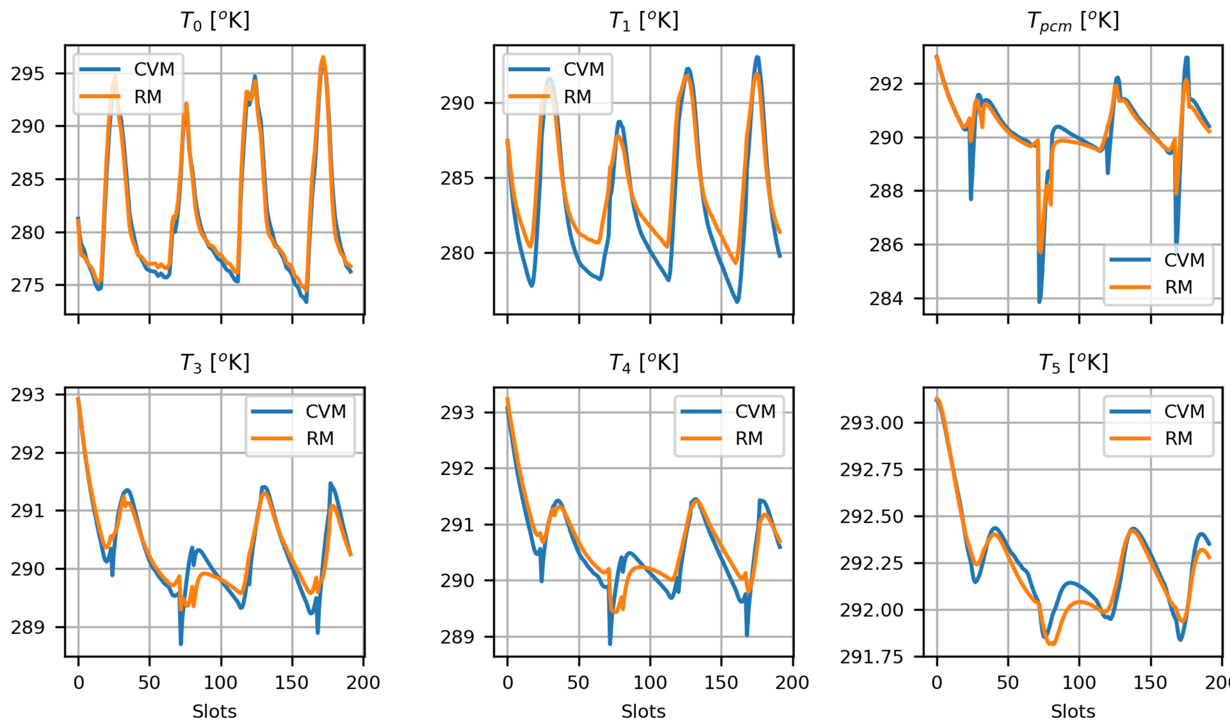

Figure 2: Control Volume Model (CMV) and Regression Model (RM) temperatures example

the mean squared prediction error for T_5, computed as $\frac{1}{n}\sum_{i=1}^{n}(T_{5,i} - \hat{T}_{5,i})^2$, being $n = 48 \cdot 88$ corresponding to the 88 days of the data set as detailed in Subsection 2.3 with a 30' time slot and being $T_{5,i}$ and $\hat{T}_{5,i}$ the real and predicted T_5 values, respectively. For a discrete-time system with state-space representation

Table 1: T_5 mean squared prediction error [°C]

	$T_{pcm} = 20\,°C$		$T_{pcm} = 23\,°C$	
City	Summer	Winter	Summer	Winter
Athens	0.010	0.022	0.011	0.010
Helsinki	0.648	0.072	0.023	0.059
Madrid	0.273	0.017	0.401	0.006
Strasbourg	0.560	0.032	0.066	0.026

$\mathbf{x}_{i+1} = f(\mathbf{x_i}, \mathbf{u_i})$, $\mathbf{x_i}$ was the model state, in our case $\mathbf{x_i} = (\dot{Q}_i, T_{pcm,i}, \cdots T_{0,i})$ and $\mathbf{u}_i$ was the action vector, pos_i in our case, as in Eq 1, at slot time i. Considering that MPC predicted the action vectors over the next prediction horizon slots $N = H/\delta$, it was convenient to represent these predicted sequences as:

$$\begin{aligned}
\mathbf{u}_{i:N+i} &= \left[\mathbf{u}_{i|i}, \mathbf{u}_{i+1|i}, \cdots \mathbf{u}_{i+N-1|i}\right] \\
\mathbf{x}_{i:N+i} &= \left[\mathbf{x}_{i|i}, \mathbf{x}_{i+1|i}, \cdots \mathbf{x}_{i+N-1|i}\right]
\end{aligned}$$

where $\mathbf{u}_{i+j|i}$ and $\mathbf{x}_{i+j|i}$ were the action and state vectors at slot $i + j$ as predicted at i.

As predictive control was based on minimising a given performance cost over the predicted sequences, that cost had a general expression as

$$J_i = \sum_{j=0}^{N-1} C(\mathbf{x}_{i+j|i}, \mathbf{u}_{i+j|i})$$

where C was our particular cost function. Finally, the optimal control sequence could be stated as an optimisation problem on J_i as

$$\mathbf{u}^*_{i:N+i} = \arg\min_{\mathbf{u}} J_i \tag{2}$$

subject to particular action and state constraints. Another MPC related parameter was the step size (k). Once an optimal sequence was obtained, $\mathbf{u}^*_{i:N+i}$, one could decide to iterate at the next slot or skip some steps (k) to decrease the computational load. In this case, the next optimisation to be solved was $\mathbf{u}^*_{i+k:N+i+k}$.

Finally, considering that in our case the cost function C was directly the value of the heating or cooling thermal load $\dot{Q}$, the optimisation problem was formulated as

$$pos^*_{i:i+N} = \arg\min_{\mathbf{pos}} \sum_{j=0}^{N-1} \dot{Q}_j$$

subject to the constraints represented in Eq. 1 and the weather forecast conditions $T_{ext,j}$ and $S_{rad,j}$ during the receding horizon, being $pos^*_{i:i+N}$ the optimal predicted PCM activations during the same horizon.

2.3. Case studies

In this subsection, a full description of the analysed case studies is given. First, the different tested climatic conditions are given in point 2.3.1. Moreover, the different melting temperatures of the PCM implemented into the dynamic system are detailed in point 2.3.2.

2.3.1. Description of analysed climatic conditions

The performance of the different control algorithms used to operate the dynamic system were tested under four different climatic conditions: Athens, Helsinki, Madrid and Strasbourg.

- Athens was selected as it is considered as the typical space heating and cooling city in south Europe. It presents a Csa climate according to Köppen-Geiger climatic classification [35], and belongs to Zone 1 in the report "Towards nearly zero-energy Buildings" of PVsites European H2020 project [36].

- Helsinki was selected as it is considered a typical space heating in northern Europe, belonging to Zone 5 with Dfb climatic conditions.

- Madrid presents a Cfb climatic conditions and belongs to Zone 2. It was selected because of its continental dry conditions.

- Strasbourg was selected as it is defined as typical space heating city in central Europe. It presents a Cfa climatic conditions.

For the corresponding location, we obtained the external temperature and the global horizontal irradiation values from the EnergyPlus Weather Format (EPW) derived from Typical Meteorological Year (TMY) files [37], generating 88 days sets for winter (including December, January and February data) and summer (from June to August). Warm up periods of 15 days are considered for both heating and cooling seasons, meaning that the performance of the analysed control systems is quantified for the following 63 days of each season. Finally, indoor set points temperatures were fixed to T_{SP}=20 °C for winter and T_{SP}=24 °C for summer.

2.3.2. Influence of PCM melting temperature

The selection of the PCM implemented into the proposed technology, specially the chosen phase change temperature, had a crucial impact on the performance of the whole system for each climatic conditions, building system, and space heating and cooling demand profile. In fact, there was an optimum PCM melting temperature for each case study and season as stated in [8; 9].

- In winter: Increasing the melting temperature of PCM would reduce the number of days per year in which the PCM can be charged, however in the days it can be successfully charged, it can provide more space heating supply. On the other hand, reducing the melting temperature of PCM would increase the number of days in which PCM is active, but with limited heating potential.

- In summer: Similarly, the lower the PCM melting temperature, the higher the cooling benefits that it can provide if successfully solidified during night time, and the less the number of days the PCM can be solidified (charged) per season.

In this paper, two different phase change temperatures were tested for each case study (T_{ppc}): 20 °C and 23 °C. It has to be noted that these values are peak melting temperature, as phase change is distributed over 4 K as described in Subsection 2.1

3. Results and discussion

This section details the performance results of the three control mechanisms under study: On-Off, Tabu search, and MPC, when applied to the different case studies. We provide average results as well as performance examples in particular scenarios, proving the benefits of the smart control techniques.

3.1. Performance of the On-Off control policy

Table 2 shows the best possible activations (times when *pos* is set to 1 or 0) of the dynamic PCM system using the On-Off control policy, for each analysed climatic conditions and PCM melting temperature. Regarding summer period, results showed that the system was able to operate in all regions with the two tested PCM. In all cases, the algorithm decided to move the PCM facing outdoors late at night, so the PCM was exposed to lowest possible temperature during night, and prevented to move the polymeric sheet (see Fig. 1) before it was cooled down. Later in the morning, the PCM was moved back to face indoors before the solar irradiation could heat it up.

Furthermore, regarding winter period, the On-Off control policy depended strongly on the climatic conditions and PCM melting temperature. In that sense, none of the possible On-Off periods provided better results than the static system in the climates of Strasbourg and Helsinki. However, under Madrid climatic conditions, the control could take profit to move the PCM outdoors at 15:00 to absorb solar energy and to move it back at 17:00 for a PCM melting T_{ppc} =20 °C. Such a benefit was not possible for T_{ppc} =23 °C. Finally, Athens used the dynamic ability of the On-Off policy at fixed set times for the whole seasons, when using both T_{ppc} (20 °C and 23 °C).

Figure 3 shows the On-Off policy performance, in terms of heating load (MJ/season), at Athens in winter, for every of the 1,128 possible On-Off periods in case of using T_{ppc} =20 °C. As shown in the figure, the minimum heating load was achieved when PCM was moved to face outdoors at 13:00 and moved back to indoors at 16:30.

Table 2: Best On-Off period

	T_{ppc} =20 °C		T_{ppc} =23 °C	
City	Summer	Winter	Summer	Winter
Athens	1:00-7:30	13:00-16:30	2:00-7:30	14:00-16:00
Helsinki	1:30-7:00	0:00-0:00	2:00-6:30	0:00-0:00
Madrid	0:30-10:00	15:00-17:00	2:00-9:00	0:00-0:00
Strasbourg	1:00-8:00	0:00-0:00	2:30-7:00	0:00-0:00

3.2. Performance of Tabu search control

Figures 4 and 5 show the performance of Tabu search during both winter and summer periods. These figures are divided into three parts, the first one shows the daily heating or cooling load per squared meter in cases when the system is always static (Off), controlled with the On-Off algorithm, or controlled with Tabu search. Moreover, the weather conditions (outdoor ambient temperature and vertical solar irradiation on south orientation) are shown in the second part of the figures. Finally, the third part of the figures presents the PCM temperature in response to the different controls, as well as the activation periods (when $pos = 1$) of On-Off and Tabu search control algorithms.

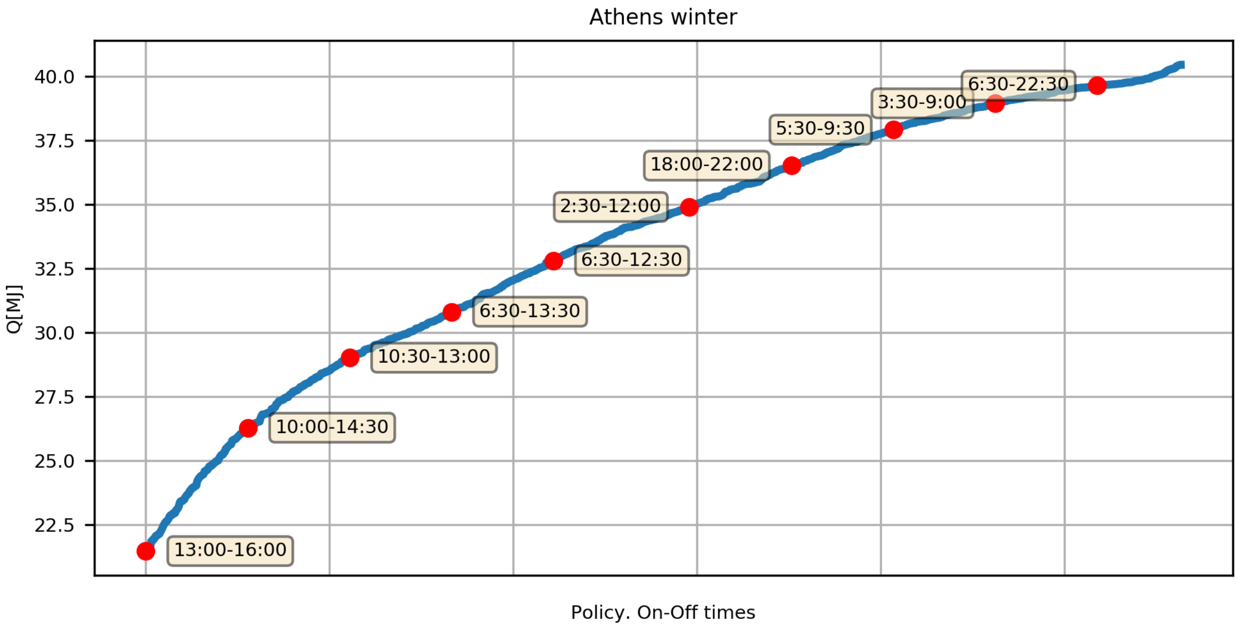

Figure 3: Heating load (Q) for some On-Off periods in Athens winter. T_{ppc} =20 °C.

Regarding winter period, Figure 4 presents the response of the control policies of ten winter days when implemented in Athens with T_{ppc} =20 °C. The results showed two clearly differentiated periods in terms of performance of the dynamic PCM system. In the first period (days from 40 to 42), solar irradiation was enough to melt the PCM when this was exposed to face outer part of insulation, thus providing higher benefits in comparison to a static system (heating load is negative in this period). Slight variations could be observed between Tabu search and On-Off control. Tabu search moved the PCM more times during the sunny hours, increasing the benefits of the dynamic technology in sunny days as it charged more continuously the internal layer of bricks. Moreover, there was a second period (42 to 45), when the solar irradiation was weak and not enough to charge the PCM. In these type of days, the PCM was cooled down if moved outdoors (to less than 14 °C). Tabu search could advance this malfunctioning by fixing the system during this period. On the other hand, On-Off policy had to follow the seasonal predetermined times to move PCM outdoors, resulting in a high heating load.

Under summer conditions, both Tabu search and On-Off control algorithms provided high benefits in comparison to leaving the PCM static as shown in Fig. 5. In this figure, the performance of the three control algorithms were compared for the case of ten summer days of Madrid when using T_{ppc} =23 °C. On the one hand, in case of having static PCM (Off strategy), the PCM was always above its melting temperature, therefore it was not being cycled. On the other hand, when the PCM was able to be moved (Tabu search and On-Off) the system daily charged and discharged the PCM, providing significant cooling benefits. Tabu search took advantage from its ability to adapt its activations every day. In the selected days

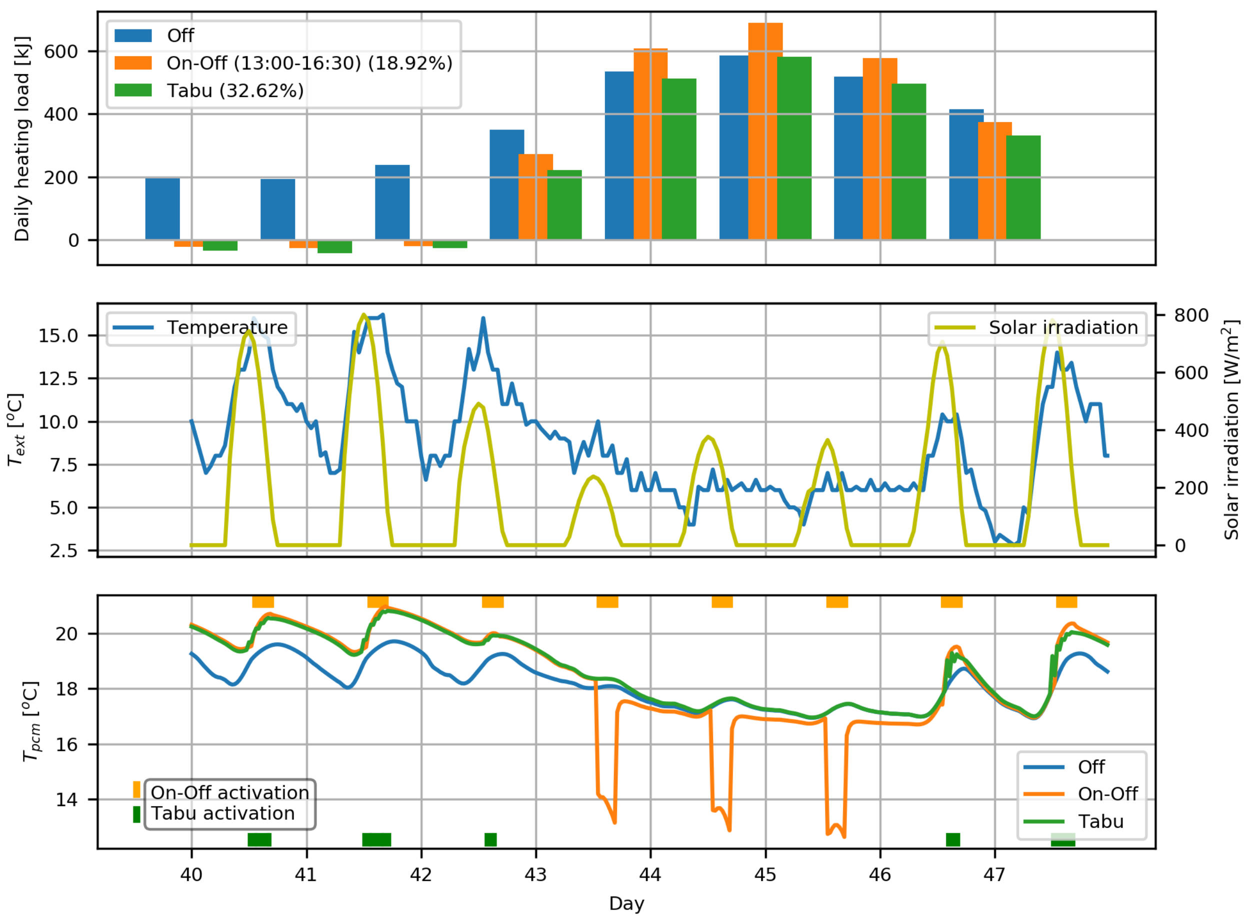

Figure 4: Example of performance of Tabu search algorithm in Athens during winter period. $T_{ppc} = 20\,^{\circ}\mathrm{C}$.

showed in Figure 5, Tabu search took more profit from colder nights (as showed in day 38 and 39) to move several times the PCM and therefore also cooled down the internal layer of bricks.

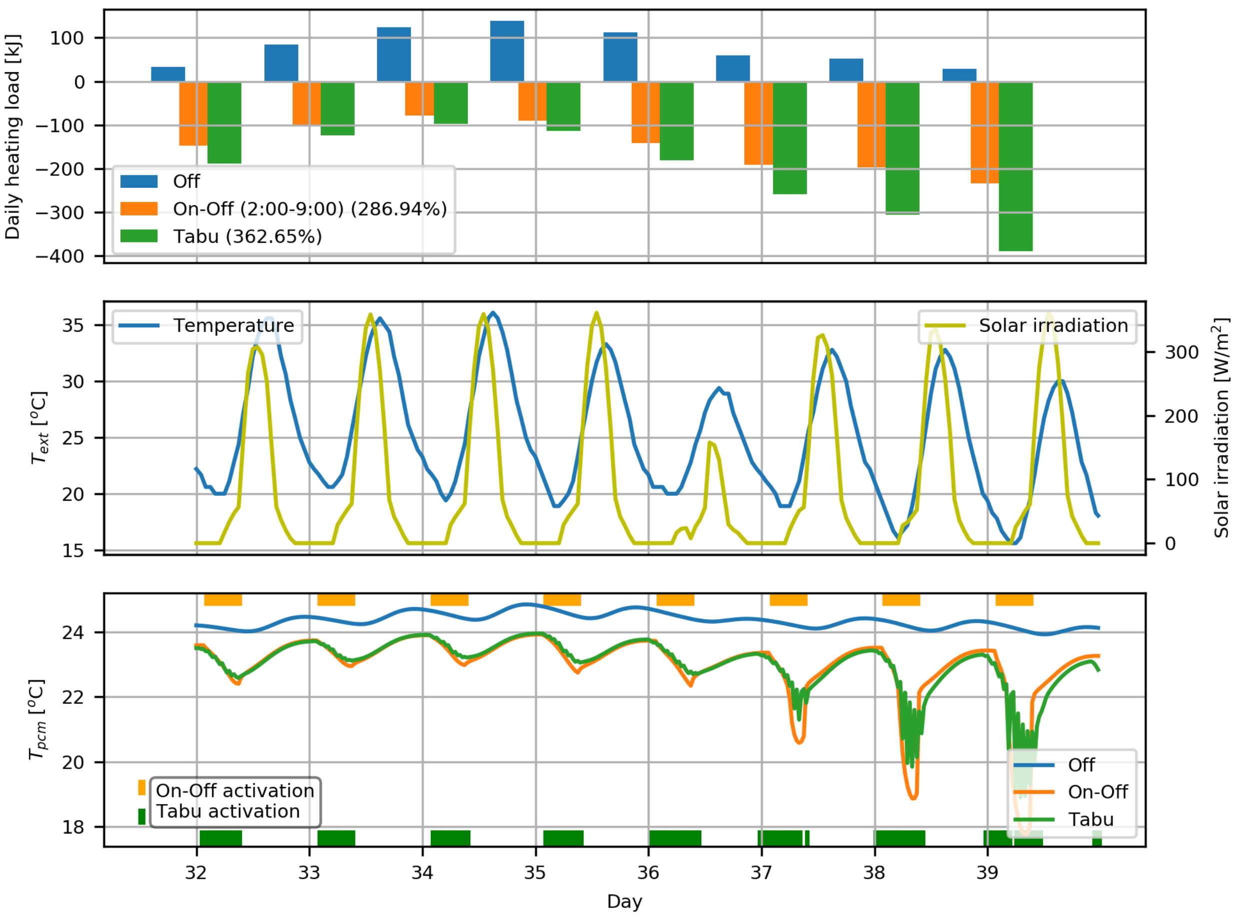

Figure 5: Example of performance of Tabu search algorithm in Madrid during summer period. $T_{ppc} = 23\,°C$.

Other than explaining in detail how the system was controlled using the activations provided by Tabu search, this section also quantifies the energy benefits of using this control algorithm in comparison to On-Off and to a static policy. In this regard, Table 3 shows the average daily cooling consumption during the whole summer period for each case study. The use of Tabu search increased the benefits of the system in all analysed cases, specially when using $T_{ppc} = 20°C$, as shown in case of Athens. Here, the On-Off policy could not obtain significant benefits when compared to the static system (less than 2%), however, these benefits were boosted up to more than 26% when using activations from Tabu search. Furthermore, in case of Madrid the system was already achieving significant benefits when applying On-Off policy as cooling consumption were negative (meaning that each squared meter of system did not transfer heat from outside, but it released heat to outdoor environment). The Tabu search control increased this cooling effect. It has to be noticed that, in this study, only heating and cooling loads from conduction through the building envelope

Table 3: Overall summer results. Average cooling load (kJ/day · m^2)

	$T_{ppc} = 20°C$			$T_{ppc} = 23°C$		
City	Static	On-Off	Tabu	Static	On-Off	Tabu
Athens	180	177	132	180	94	73
Helsinki	-113	-743	-1,002	-115	-393	-881
Madrid	11	-250	-316	12	-201	-301
Strasbourg	-141	-657	-820	-140	-359	-698

were considered, and in real buildings, other loads are present, such as infiltration, internal loads, thermal bridges from elements, and solar gains from glazed surfaces.

Regarding the benefits during winter period, Table 4 shows the average heating consumption for each case study under the different control policies. First, the results showed that the system was useless for heating purposes in climates similar to Strasbourg or Helsinki, as it was not able to provide any benefits at least when integrated into this constructive system. The low outdoor temperatures and solar irradiation registered in these regions made impossible to melt the PCM. On the other hand, the system provided significant thermal benefits in Athens even when controlled with just the On-Off policy, achieving reductions of 17.5% when using PCM with $T_{ppc} = 20°C$ and 7% when $T_{ppc} = 23°C$. In the case of Athens, these reductions were significantly improved when the system control was based on the sequence provided by the Tabu algorithm, achieving 32% and 19%, respectively. Finally, the results from Madrid demonstrated that the selection of the appropriate PCM in terms of its peak phase change temperature was critical, as the system could not provide benefits, when controlled with On-Off policy, if the selected PCM was the one with $T_{ppc} = 23°C$, while it reduced a 4% the heating consumption when using the PCM with $T_{ppc} = 20°C$. However, Tabu search control provided significant benefits when using both PCM.

Table 4: Overall winter results. Average heating load (kJ/day · m^2)

	$T_{ppc} = 20°C$			$T_{ppc} = 23°C$		
City	Static	On-Off	Tabu	Static	On-Off	Tabu
Athens	332	274	225	332	309	268
Helsinki	414	414	414	414	414	414
Madrid	469	451	420	469	469	431
Strasbourg	487	487	487	487	487	487

3.3. Performance of MPC control algorithm

In this subsection, both MPC and Tabu search control performances are compared. Table 5 presents thermal loads during both heating and cooling periods for all the analyzed climates, implementing a PCM with $T_{ppc} = 20°\text{C}$, when the system was controlled with Tabu control algorithm and with MPC with two different horizons: 2.5 and 5 hours. Results showed that MPC performed similarly to Tabu search, and only small differences could be observed between the performance of those two control algorithms, being slightly better the ones obtained from Tabu, except in the case of Athens during summer period. The results indicated that extended horizons in MPC were useless, as better results were obtained when using a horizon of 2.5 hours in comparison to 5 hours. This was because the MPC control algorithm could not directly use the developed finite control volume model to evaluate the response of the system for a given set of actions, as it was non linear. Instead of the finite volume model, MPC had to use the linear regressions detailed in Subsection 2.2.3 with the accuracy provided in Table 1. Those deviations, when accumulated during the receding horizon, limited an optimal performance of MPC, giving better results for shorter horizons. Nevertheless, the authors want to highlight that even with this limitation, MPC could achieve similar values to those obtained by Tabu, with just using forecast data for the following 2.5 hours, while Tabu algorithms used the prediction of solar irradiation and outdoor temperature for the following 24 hours, being more sensitive to inaccuracies from the weather predictions. Furthermore, the computational cost of MPC was extremely lower. To compute an MPC prediction for the incoming slots, a few CPU seconds were required, while search for the complete next day by Tabu sequence took several minutes. It is worth to mention that those CPU times refer to a standard 3.3 GHz CPU. A deployment based on micro-controllers could increase the computing time in more than an order of magnitude. Considering such a time performance, together with the fact that our control implementation uses multi-platform open-source software (Python and SCIP Optimization Suite [33]), it can be easily integrated into any BEMS (Building Energy Management Systems) platform.

Table 5: Comparison of Tabu and MPC performance. Average heating/cooling load (kJ/day $\cdot$ m^2)

	Summer			Winter		
		MPC			MPC	
City	Tabu	H=2h 30'	H=5 h	Tabu	H=2h 30'	H=5 h
Athens	132	129	135	245	251	256
Helsinki	-1002	-979	-965	414	414	414
Madrid	-316	-276	-265	420	420	420
Strasbourg	-820	-752	-745	487	487	487

4. Conclusions

In this study, two smart control algorithms based on weather forecast were developed to operate a novel dynamic phase change material wall system. The dynamic phase change material technology relies on the ability to change the position of a phase change material layer with respect to the insulation layer, to increase the use of solar heat for space heating during winter, and the use of night free cooling during summer. The decisions to when locate PCM facing indoors or outdoors were critical to maximise benefits and avoid malfunctioning both in heating and cooling periods. The developed smart control algorithms were based on forecast weather data and followed the set of activations based on Tabu search and MPC. These two control algorithms were compared under the climates of Athens, Madrid, Strasbourg, and Helsinki, against other two control policies without the use of forecast weather data: always static and an On-Off policy.

Results indicated that during summer, both smart control algorithms could strongly improve the performance of an On-Off policy in all analysed cities, reducing the average cooling load of the system even to negative values. Moreover, during winter season, both smart control algorithms improved the performance of the system only in Athens and Madrid climates, as the system could not provide heating benefits neither in Strasbourg nor in Helsinki. Results also showed that the use of smart control algorithms in winter was even more critical than in summer, as it prevented the system to move the phase change material to face outdoors in days with low solar radiation, which would provide extra heating loads.

In both seasons, both smart control algorithms provided similar benefits even though, the use of a linear approximation for the system model, required to tackle the MPC formulation, degraded its performance for receding horizons beyond a few hours (best results were obtained with 2.5 hours of horizon). Moreover, it has to be highlighted that even with this limitation, model predictive control achieved similar values as the ones obtained by sequence from Tabu search, even consuming significant less computational resources, and using forecast data for the following 2.5 hours and not for the following 24 hours, as Tabu search required.

Finally, the present study demonstrates that both developed smart control algorithms could be implemented with reasonable computational resources to successfully operate the activations of the novel dynamic phase change material wall system, maximising its benefits in both summer and winter periods, and avoiding its possible malfunctioning. The successful implementation of such smart control algorithms provided an important advance on the use of smart control in thermal energy storage systems based on weather forecast, which contributes significantly in the field of sustainable energy systems.

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