# Day-ahead predictive control of heat pump and energy storage systems with integrated photovoltaics

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**Abstract**

Thermal energy storage (TES) became a crucial element in building heating, ventilation, and air conditioning (HVAC) systems. The feature of adding energy flexibility for performing optimal heating control, load shaving/shifting, and energy price-dependent management are among the TES essential foreseen roles. However, driving TES within a realistic operation environment to fulfill these targets might not be straightforward. This need becomes critical when a renewable energy system, with intermittent behavior, is integrated or when load fluctuations are present. This work represents a simulation study for one-day ahead predictive management addressing the heating cost optimization for an HVAC-integrated heat pump with a photovoltaic (PV) system. Using real data collected for a building situated in University College Dublin in Ireland, the proposed TES predictive management strategy using a PV partially-powered heat pump could show a heating cost reduction of more than 20% in winter compared to the baseline scenario where no optimization-driven TES exists.

*Keywords: Thermal energy storage, predictive management, photovoltaic, HVAC*

## 1. Introduction

Integrating diverse renewable energy sources (RES) and distributed energy assets for decarbonizing the energy utilization in buildings has become essential. However, the intermittent nature of RES, coupled with dynamic energy demands, has underscored the necessity for flexible energy management strategies. This imperative arises from the pursuit of not only enhancing the efficient utilization of available local energy resources but also mitigating energy expenses, reducing electricity costs, and maximizing the integration of RES in buildings for heating and cooling purposes. At the heart of this challenge lies the optimization of thermal energy storage (TESs) and controllable assets, where safety and efficiency are paramount. Thus, the quest for energy flexibility in buildings is driven by the dual goals of sustainability and economic viability, positioning it as a crucial means to navigate the complexities of modern energy ecosystems.

### 1.1. Background

In building energy management systems (BEMS), TES can be crucial where heating and cooling demands and energy prices fluctuate throughout the day. By integrating TES into Heating, Ventilation, and Air Conditioning (HVAC) systems, BEMS can mitigate these fluctuations and offer a cost-effective load satisfaction (Reza et al., 2015). Advanced control strategies are essential for optimizing the charge and discharge cycles of TES systems, ensuring efficient energy utilization while maintaining overall system reliability. Effective TES management is particularly critical in applications such as building energy optimization and the integration of RES. Traditional rule-based control strategies rely on predefined set-point adjustments to regulate charging and discharging cycles (E. Saloux and J.A. Candanedo, 2020). However, these methods often struggle to adapt to fluctuating operating conditions, resulting in suboptimal performance. In contrast, advanced approaches such as optimization-based control dynamically optimize TES operation by leveraging real-time data and forecasted energy demand and weather. In this context, RES intermittent behavior could also be mitigated with an optimization-driven TES (Ryozo Ooka and Shintaro Ikeda, 2015).

### 1.2. Previous works

Elkhatat et al. (2023) highlighted the need to use TES in combination with renewable energy, because of their need for enhanced reliability and grid stability. Suggestions are that future work should focus on cost reduction. Arteconi et al. (2013) acknowledged that the inclusion of TES with heat pumps could shift the electricity demand and reduce the energy costs. Gallo and Capozzoli (2024) reviewed advanced control and optimization


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strategies for energy flexibility in renewable energy communities, concluding that smart control, predictive management, and integration of storage are key for flexibility and renewable use.

Joe and Karava (2019), Hernandez-Matheus et al. (2022), and Brandi et al. (2022) show different building control strategies like Deep Reinforcement Learning (DRL) and Model-Predictive Control (MPC). Their use led to improved flexibility and response to a dynamic environment, although DLR does not depend on large data sets.

Yu et al. (2024) proposed an optimization-based analysis of coupled hybrid energy systems, integrating control of Photovoltaic Thermal (PVT), heat pump, and TES. The work demonstrated operational flexibility and energy savings. In addition, Fiorotti et al. (2024) used an optimization model for day-ahead scheduling of PVT and TES systems. The joint optimization of electrical thermal loads led to increased self-consumption and cost savings, which shows that coordinated control reduces grid dependency.

Panda et al. (2022) compared residential demand-side management models and optimization techniques, concluding that optimization methods like MILP, GA, and PSO enhance energy efficiency. Over and beyond, they suggest integration with renewables and storage, because of the large flexibility potential. Habib et al. (2024) complemented that data-driven optimization enhances overall energy efficiency and flexibility from distributed resources, reduces operational cost and emissions by an optimization-driven case study.

### 1.3. Proposed method

This study presents a simulation-based assessment of thermal energy storage (TES) control within a building's heating substations. By implementing hourly optimal charging cycles, the objective is to leverage available online data sources, such as weather and energy price forecasts, to predictively optimize TES charging and discharging schedules. Utilizing these forecast services enables the extension of optimal HVAC (heat pump) control up to 24 hours in advance, thereby enhancing indoor thermal comfort, improving the utilization of TES storage capacity, and minimizing heating costs.

## 2. Method

This study proposes an optimal control-based methodology for managing TES to enhance energy efficiency in building heating systems. The approach performs day-ahead scheduling of TES operations using online weather forecasts and load predictions combined with optimization algorithms. Based on these inputs, a 24-hour charging plan for a water-tank TES is generated. The system employs an air-source heat pump (HP), partially powered by a photovoltaic (PV) system, with TES control achieved through hourly adjustment of the HP condenser temperature setpoint. The overall system configuration is illustrated in Figure 1.

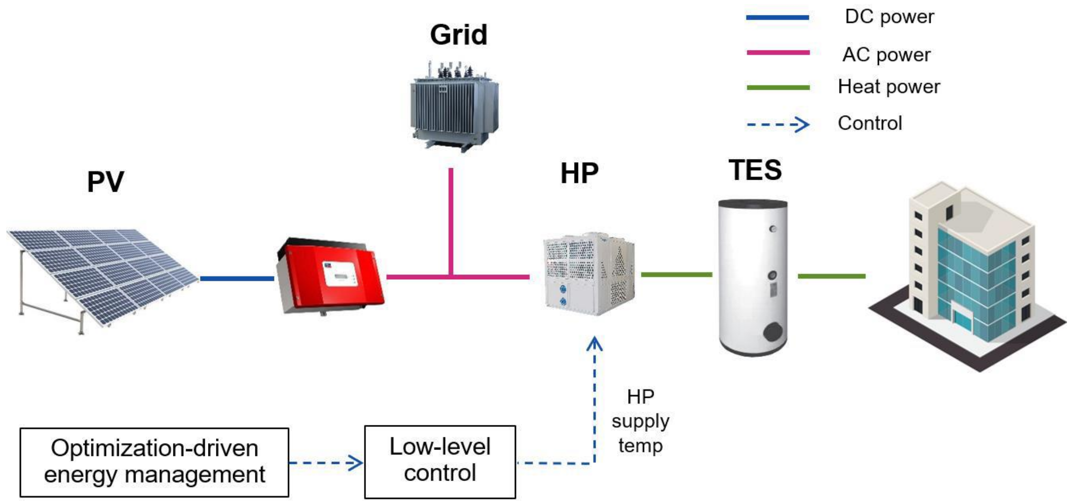


**Figure 1: proposed optimization-driven HP/TES for building heating**

### 2.1. Assumptions

This work is part of the development of an optimal heating management system. It presents a case study on a residential building in an educational campus, in the framework of the European research project HYSTORE.

The TES is combined with an air-to-water heat pump for heating in comparison with a baseline, which is a conventional fossil-based system. The implementation of the optimization-driven HP-TES control, which is simulated in MATLAB, is compared to the baseline scenario with respect to energy cost and photovoltaic energy self-consumption. The limitations of this paper are the following:

- The heating consumption and the domestic hot water of the residential building are presented individually in the SCADA system, where data is taken from. The household electricity and water consumption are not included in the modelling.
- The study is limited to the usage of sensible energy only. No other energy storage technologies are covered.
- The paper excludes any modelling activity for building physics (materials, isolation, geometry, etc.) as this information is already included in the heating consumption data patterns.
- Costs related to the investment in the additional heating infrastructure proposed within the actual scenarios is not considered.
- The total heat demand in the residential building was roughly approximated to be 70% of the total gas consumption.

## 2.2. One-day ahead heat pump/energy storage control

The proposed validation framework for the one-day ahead heating management is presented in Figure 2. Based on some set of data inputs that incorporate sensor data from the building management system (BMS), weather, and electricity price forecasts, and dynamic system modeling, the optimization-driven control of HP-TES can be initiated. MATLAB was chosen as a simulation and optimization platform thanks to its powerful predefined functions. The simulation is designed to display the HP operational performance (e.g., coefficient of performance (COP)), TES SoC dynamics, and electric power flow direction in the building-grid context.

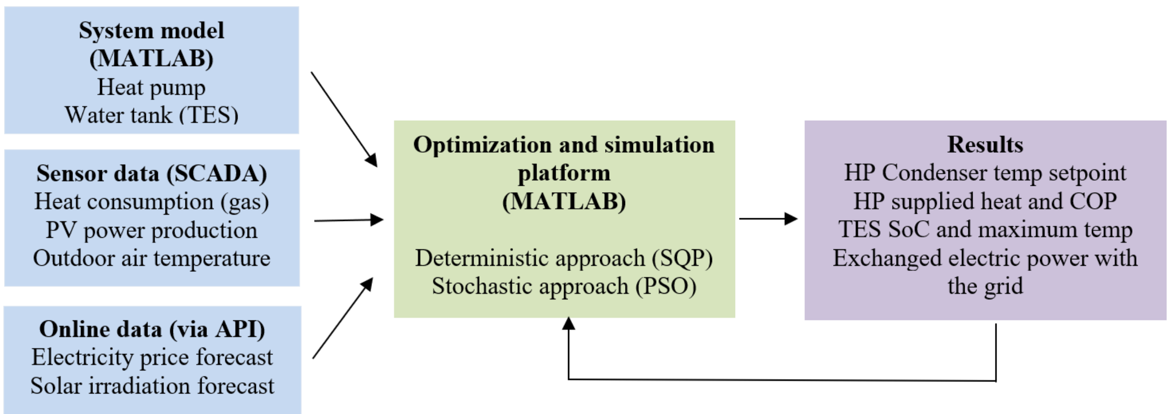


**Figure 2: Workflow of the proposed strategy**

## 2.3. System modelling

For system modelling, the calibrated Carnot equation was chosen to model the HP and multi-node stratified water tank to model TES. In previous work, Habib et al. (2024) selected one representative week for every season from the data. The gas consumption, solar production, outdoor temperature, and electricity prices for these weeks are imported to MATLAB. The prices are taken from EMBER, and sensor data from BMS.

In Figure 3, $T_{source,in}$ is the inlet temperature of outdoor air to the evaporator and $T_{source,out}$ is the outlet temperature of the evaporator. $T_{sink,hot}$ is hotter than $T_{source,in}$. For the system modelling, assume that $T_{sink,hot}$ is the same as $T_{sink,cold}$, and will be named $T_{sink}$.

For the heat pump, a coefficient of performance (COP) can be calculated as

$$COP = \frac{Q_{HP,out}}{P_{net,in}} \quad \text{(eq. 1)}$$

where $Q_{HP,out}$[kW] is the desired output heat and $P_{net,in}$ [kW] is the net power input from the electricity grid and PV production to the compressor in the heat pump, as seen in Figure 3.

The heat removed from the cold environment to the evaporator in the heat pump can be calculated using equation 2, neglecting heat waste in sub-components in the heat pump.

$$Q_{HP,in} = Q_{HP,out} - P_{net,in} \quad \text{(eq. 2)}$$

Where $Q_{HP,in}$ [kW] is the input heat to the evaporator in the heat pump, as seen in Figure 3.

Another way to calculate the COP is to use equation 3, where the COP depends on the $\eta_{HP}$, the heat pumps sink temperature and the inlet source temperature.

$$COP = \eta_{HP} \frac{T_{sink}}{(T_{sink} - T_{source,in})} \quad \text{(eq. 3)}$$

Where $\eta_{HP}$ is the empirical coefficient that adjusts the ideal Carnot COP to the real COP. In this study, the empirical coefficient is a fixed value at 0.16, and the heat pumps' sink temperature $T_{sink}$ [°C] assumes to be the heat pump's condenser temperature. The condense temperature is the control variable in the model and the variable in the objective function in MATLAB. The source temperature $T_{source,in}$ [°C] is the outdoor temperature in Ireland, taken from the SCADA during the different weeks that is analysed.

To determine the water temperature in the thermal energy storage at each node *i*, the following heat differential Equation 4 is used,

$$m_i \cdot C_p \cdot \frac{dT_i}{dt} = Q_{in,inital} + Q_{conv,i} + Q_{cond,i} - Q_{out,inital} - Q_{loss,i} \quad \text{(eq. 4)}$$

Where at each node *i* , $m_i$ [kg] is the water mass , $C_p$ is the specific heat capacity of water [kJ/kg, K] and delta $T_i$ is the change in temperature in the thermal energy storage; $Q_{in,inital}$ [kW] is the input heat to the TES (equivalent to the output heat from the heat pump) and $Q_{out,initial}$ [kW] is the output heat from the TES and should be equal to the building's heat demand [kW]; $Q_{conv,i}$ [kW] is the heat loss or heat gain through convection and is formulated in Equation 5. The next parameter is the $Q_{cond,i}$ [kW], which is the heat transferred through conduction between node *i* & (i-1) and node i & (i+1), and is formulated in Equation 7. The last parameter is the $Q_{loss,i}$ [kW] is the heat loss through the stainless-steel tank wall and is formulated in Equation 8. The heat loss or heat gain through convection is formulated in Equation 5:

$$Q_{conv,i} = (\chi_{up} \cdot (m_{prick,in} - m_{prick,out}) \cdot C_p \cdot (T_{i-1} - T_i)) - (\chi_{down} \cdot (m_{prick,in} - m_{prick,out}) \cdot C_p \cdot (T_i - T_{i+1})) \quad \text{(eq. 5)}$$

where $\chi_{up}$ and $\chi_{down}$ is the flow indicator and is presented in Equation 6. The $m_{prick,in}$ [kg/s] is the inlet water flow to the water tank and $m_{prick,out}$ [kg/s] is the outlet water flow of the water tank. $C_p$ is the specific heat capacity of water [kJ/kg, K]. The temperature difference between the previous node and node *i* $(T_{i-1} - T_i)$ [°C] and the following node and node i $(T_i - T_{i+1})$ [°C].

$$\chi_{up} = \begin{cases} 1 \; if \; m_{prick,in} > m_{prick,out} \\ 0 \; else \end{cases}, \chi_{down} = \begin{cases} 1 \; if \; m_{prick,out} > m_{prick,in} \\ 0 \; else \end{cases} \quad \text{(eq. 6)}$$

The heat transferred through conduction between node i & (i-1) and node i & (i+1) is formulated in Equation 5,

$$Q_{cond,i} = \frac{k_w \cdot A_{tank}}{dX}(T_{i-1} - T_i) - \frac{k_w \cdot A_{tank}}{dX}(T_{i-1} - T_i) \quad \text{(eq. 7)}$$

where the $k_w$ [W/m.K] is the thermal conductivity of water, and the value being used in this thesis is $k_w$ = 0.613 [W/m.K] (Çengel, Boles and Kanoğlu, 2024). $A_{tank}$ [m2] is the tank area cross-section. The temperature difference between the previous node and node i $(T_{i-1} - T_i)$ [°C] and the following node and node i $(T_i - T_{i+1})$ [°C].

The heat loss through the stainless-steel tank wall at each node i is formulated in equation 8,

$$Q_{loss,i} = k_{wall} \cdot A_{lat} \cdot (T_i - T_{amb}) \quad \text{(eq. 8)}$$

where the $k_{wall}$ [W/m.K] is the thermal conductivity of stainless steel, and the value being used in this thesis is $k_{wall}$ = 16.2 [W/m.K] (Wang et al., 2025). $A_{lat}$ [m2] is the tank's lateral surface, excluding the top and bottom of the tank. The temperature difference between node i and the ambient temperature $(T_i - T_{amb})$ [°C]. The ambient temperature is chosen to be 23 [°C].

To calculate the water temperature at each node i, the differential equation 4 is solved numerically by using Equation 9,

$$\Delta T_i = \frac{\Delta t}{C_p \cdot \rho \cdot \pi \cdot R^2 \cdot dX} \cdot (Q_{conv,i} + Q_{cond,i} - Q_{loss,i}) \qquad \text{(eq. 9)}$$

where $\Delta T_i$ [°C] is the temperature increase at each node $i$; $C_p \cdot \rho \cdot \pi \cdot R^2 \cdot dX$ is the water mass of each node calculated with the water density $\rho$ [kg/m3], the node height dX [m]; and the water tank's radius $R$ [m].

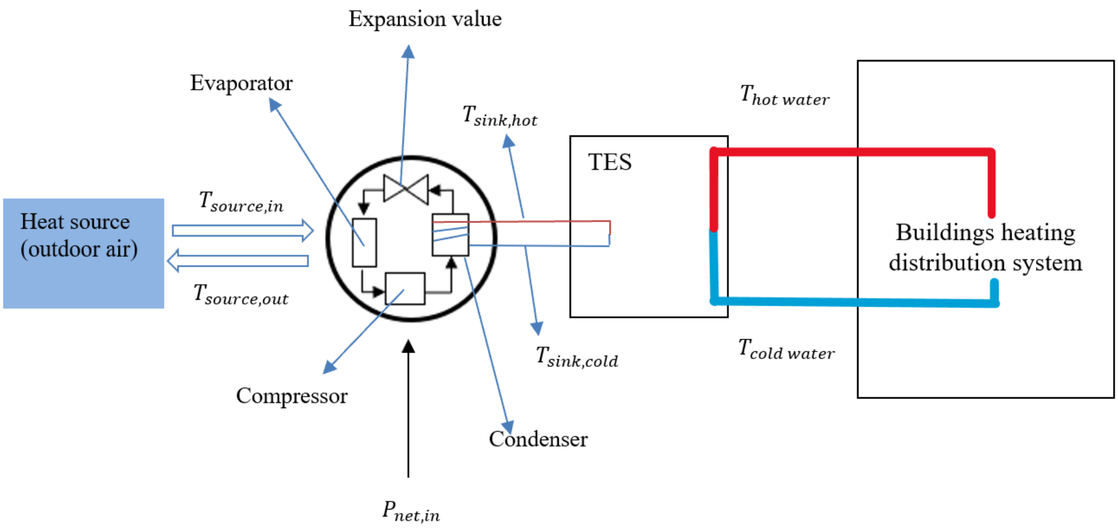


**Figure 3: The component in the heat pump, TES and temperatures.**

## 2.4. Optimization algorithms

For the optimization algorithm, two objective functions were formulated targeting two goals: either reducing the electricity cost related to the heating demand or maximizing the PV self-consumption. Two optimization algorithms were selected from two different categories, the population-based stochastic optimization method Particle Swarm Optimization (PSO), and Sequential Quadratic Programming (SQP) as a deterministic approach. The reason behind this choice is to assess the proposed method's performance against two different optimization families.

According to Habib et al. (2024), the optimization algorithm SQP starts with an initial guess for the decision variable $x$. The Lagrangian (eq. 11) is a combination of the objective function $f(x)$:

$$f(x) = \frac{1}{2} x^T Q x + F^T x \qquad \text{(eq. 10)}$$

and the weighted sum of constraint functions $h(x) = 0$ and $g(x) \leq 0$. At each time step, the algorithm forms a quadratic approximation of the Lagrangian:

$$L(x, \lambda) = f(x) - \lambda^T h(x) - v^T \, g(x) \qquad \text{(eq. 11)}$$

Minimizing the objective function is now equal to finding the $x$ that minimizes the Lagrangian. Where $Q$ and $F$ are the quadratic cost matrix and the linear cost vector, $\lambda$ is a vector of Lagrangian multipliers for the inequality constraints, $x$ is the decision variable and $\lambda$ and $v$ are Lagrange multipliers.

Unlike SQP, the population-based algorithm PSO has no evolution operators (Habib et al. (2022) ). It is initialized with a group of random solutions and then searches for optima by updating generations. These updates are based on the two equations eq. 12 and 13 and those again on the two "best" values $pbest$, the individual best solution of the particle and $gbest$, the global best of all particles.

$$v(i+1) = v(i) + c_1 \cdot r_1\big(pbest(i) - p(i)\big) + c_2 \cdot r_2\big(gbest(i) - p(i)\big) \qquad \text{(eq. 12)}$$

$$p(i+1) = p(i) + v(i+1) \qquad \text{(eq. 13)}$$

Where $i$ is the number of iterations, $v$ is the particle velocity, $p$ is the current particle (solution), $r$ are random numbers between 0 and 1 and $c$ are learning factors.

Furthermore, this study adopts two different main objective functions: electricity cost optimization and PV self-consumption. For the electricity cost optimization, the building owner aims to sell any extra PV energy production to the grid utility regardless of the TES storage capacity. The common motivation behind this strategy is that the owner would like to maximize the reward from the extra PV energy to compensate for the fees related to the system installation.

For the PV self-consumption, the building owner targets the local consumption of any extra PV production, so the sold energy will be minimized as the weather and load conditions allow. The motivation behind this is typically due to the low electricity selling prices, which push the owner to locally consume what was produced. Here, the TES storage capacity plays a decisive role. Another motivation is that the owner would like to be more independent and would like to store more energy locally.

The scope of this study is restricted to the second objective formulation - PV self-consumption - to maintain focus and avoid excessive expansion of the article's content.

### 2.5. Simulation conditions

The optimal HP–TES control is evaluated under specific environmental conditions, including heat demand, outdoor temperature, and PV power generation. These parameters, illustrated in Figure 4 for a representative winter scenario, reflect the "worst-case" conditions characterized by high heating demand and low PV energy availability.

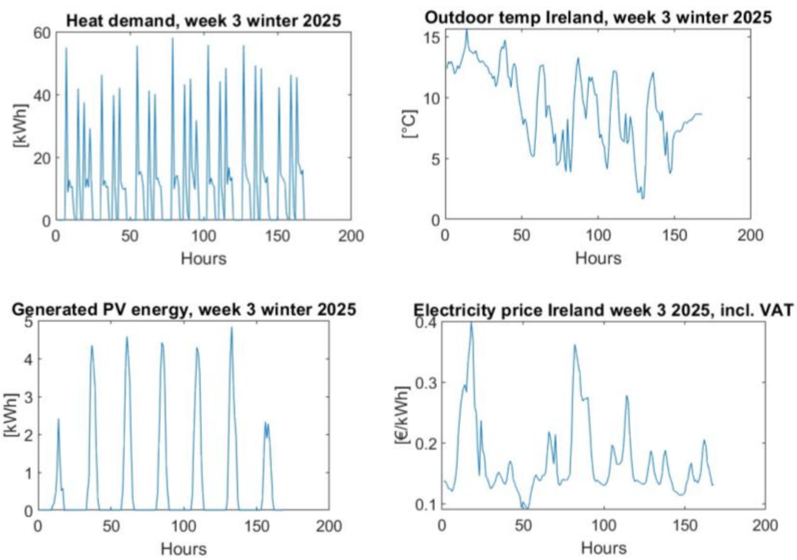


**Figure 4: Simulation conditions**

## 3. Results and discussion

This section is dedicated to showing the results of the digital simulations of the HP-TES control with the two optimization algorithms. Under the environmental conditions shown in Figure 4, the simulation of the one-day ahead optimal control of HP-TES was performed, showing the HP performance (supplied heat power, COP and condenser temperature), TES operational point (SoC and maximum temperature), in addition to the electric power exchanged with the grid (see Figures 5 and 6).

Overall, both SQP and PSO-based control algorithms could lead to a cost-effective heating solution in comparison to the baseline scenario (see Table 1) while respecting the system constraints. Depending on the chosen electricity profiles, for both buying and selling, solar irradiation levels and load, SQP showed more consistent performance across the two objective function formulations, due to the deterministic optimization mechanism. However, PSO led to the most optimized costs and stochastic patterns (see Figure 6 and Table 1). Compared are the Baseline, SQP, the cost reduction with SQP compared to gas, the PSO, and the cost reduction with PSO compared to gas. These values are shown for the different cost functions: Gas, Electricity cost, and

PV self-consumption.

The seasonal comparison of cost reduction strategies reveals significant performance differences between the baseline gas-only control, the SQP optimization, and the PSO approach. In spring, both SQP and PSO achieved substantial savings relative to the baseline, with total costs reduced by approximately 65–70%. The summer period demonstrated the highest cost reduction potential, with SQP lowering energy costs by about 83% and PSO reaching reductions of up to 86%, reflecting the enhanced influence of PV generation and reduced heating demand. During autumn, the optimization impact was moderate, yielding 39–58% reductions for SQP and 40–50% for PSO, as the diminished solar contribution and increasing heating loads constrained further improvement. In winter, cost reductions were more limited, ranging between 18% and 35%, due to the dominance of heating demand and reduced photovoltaic availability. Overall, PSO consistently achieved slightly higher cost savings than SQP across most seasons, indicating better adaptability to the nonlinear energy management problem. Both optimization methods, however, demonstrated strong potential for improving photovoltaic self-consumption and reducing dependency on gas-based heating, resulting in annual cost reductions between 20% and 85% depending on the seasonal conditions. These findings confirm that optimization-based control strategies, particularly PSO, can serve as an effective approach for enhancing energy efficiency and reducing operational costs in smart building applications.

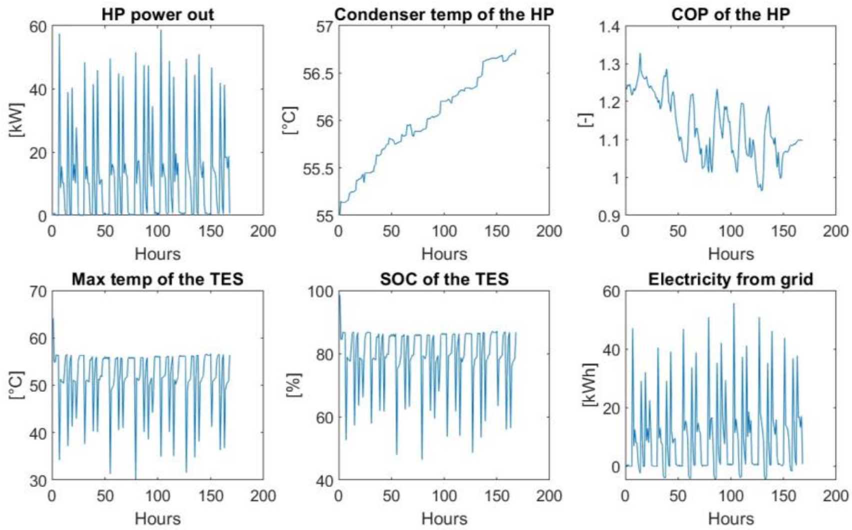


**Figure 5: PV self-consumption results from SQP for winter**

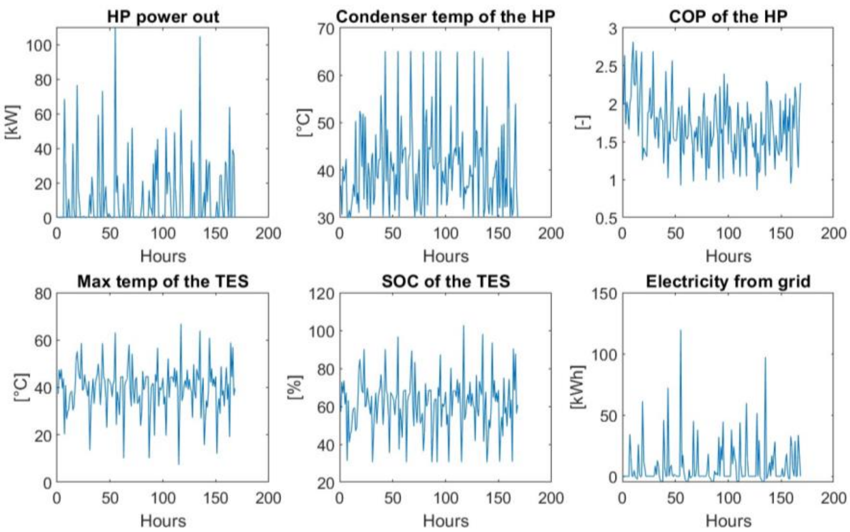


**Figure 6: PV self-consumption results from PSO for winter**

**Table 1: Results from the simulation of one week for the different seasons.**

| Scenario | Cost function | Baseline [€] | SQP [€] | Cost reduction SQP compared to gas [%] | PSO [€] | Cost reducing PSO compared to gas [%] |
|---|---|---|---|---|---|---|
| **Spring** | Gas cost | 391.31 | - | | - | |
| | Electricity cost | - | 134.79 | -65,55 | 118.77 | -69,65 |
| | PV SC | - | 133.31 | -65,93 | 133.90 | -65,78 |
| **Summer** | Gas cost | 152.15 | - | | - | |
| | Electricity cost | - | 26.16 | -82,80 | 21.72 | -85,73 |
| | PV SC | - | 25.78 | -83,06 | 22.01 | -85,53 |
| **Autumn** | Gas cost | 309.74 | - | | - | |
| | Electricity cost | - | 188.06 | -39,29 | 185.70 | -40,05 |
| | PV SC | - | 130.63 | -57,83 | 153.70 | -50,38 |
| **Winter** | Gas cost | 373.74 | - | | - | |
| | Electricity cost | - | 290.09 | -22,38 | 308.33 | -17,50 |
| | PV SC | - | 292.32 | -21,79 | 241.96 | -35,26 |

SC = Self-Consumption

## 4. Conclusion

This study presented a one-day-ahead optimal control strategy for a thermal energy storage (TES) system coupled with a partially photovoltaic (PV)-powered heat pump, aiming to minimize building energy costs while enhancing self-consumption of renewable energy. Two optimization methods, Sequential Quadratic Programming (SQP) and Particle Swarm Optimization (PSO), were evaluated across seasonal scenarios to assess performance under varying thermal and solar conditions. The results demonstrated that both optimization approaches significantly reduced operational costs compared to a conventional gas-based baseline, achieving reductions between 20% and 85% depending on the season. The highest benefits were observed in summer, where the increased PV contribution enabled up to 86% savings, while winter conditions limited the achievable gains due to elevated heating demands.

Between the two strategies, PSO consistently provided slightly superior results, particularly in handling the nonlinear dynamics of the coupled TES - heat pump - PV system. SQP, however, offered comparable performance with faster convergence in more stable operating conditions. Both methods effectively enhanced PV self-consumption, reduced grid dependency, and demonstrated the feasibility of predictive optimization for energy-efficient building operation.

Overall, the proposed control framework highlights the potential of integrating day-ahead optimization with hybrid renewable systems to achieve substantial energy and cost savings in smart buildings. Future work will focus on extending the approach to multi-day horizons, incorporating uncertainty in weather and load forecasts, and validating the method through real-time implementation on embedded control hardware.

## 5. Acknowledgements

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