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Representative period selection for flexible control strategies on a reversible heat pump in cooling mode: A comparative case study

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ABSTRACT

Rising space-cooling demand is intensifying peak electricity loads. Although reversible heat pumps are widely recognised as a key technology for building decarbonisation, it remains essential to avoid peak loads on the electrical grid and shift demand towards periods characterised by higher renewable energy availability and more favourable electricity prices. It is therefore crucial to investigate flexible control strategies that can manage peak electricity demand and overall energy use, while promoting the self-consumption of energy from renewable sources and ensuring indoor comfort. In this context, identifying week cycles representative of a full year or season allows to assess heat pump behaviour and infer the impact of flexible control strategies on its annual energy performance, especially when annual analyses are not feasible or practical, as in lab or field experiments. This study analyses four representative day selection procedures under two day-ahead price-based control strategies applied to a reversible heat pump operating in cooling mode. A comparative analysis is conducted for three southern Europe locations. The dynamic simulations include the building, the GSHP coupled with radiant panels, and a separately controlled dehumidifier. The results indicate that the clustering method is the most effective method at representing key performance indicators across the climates, whereas the proposed consecutive day selection method provides the most accurate absolute values for extrapolated electricity cost and energy consumption.

1. Introduction

The need to reduce the carbon footprint of energy consumption in buildings — which currently accounts for 36% of greenhouse gas emissions in the EU alone — will lead to a significant increase in electricity consumption in the building sector, both in absolute terms and as a proportion of total energy consumption. In the Stated Policies Scenario (STEPS), electricity is projected to account for over 40% of energy consumption in buildings by 2030, rising to over 50% by 2050 [1]. The global energy system is currently facing a series of unprecedented challenges, driven by two main factors: the ongoing rise in global temperatures and the rapid growth of variable renewable energy sources. Record-breaking heatwaves in 2023 and 2024 caused electricity demand for space cooling to reach record highs, stressing power grids worldwide [2]. Since the year 2000, space cooling has increased consistently by around 4% each year. It is estimated that this growth will continue at an average annual rate of 3.2% until 2050 [1]. This recent evidence indicates a broad, long-term trend in energy use patterns. Clearly, there will be a significant shift in the balance of energy consumption in the building sector by end-use [3], with a transition from space heating to space cooling and appliances over the next few decades. Furthermore, the widespread adoption of heat pump systems is also shifting the demand for heating away from fossil fuels and towards electricity.

The rapid growth air conditioning is the primary driver of increasing peak electricity demand from buildings in both emerging and developed countries [4]. Consequently, there has been an increased focus on strategies improving the thermal performance of buildings during the summer months, ensuring thermal comfort while reducing the cooling demand. Load shifting over time can also improve power system stability by reducing the daily variation in residual load, i.e. the total electricity demand minus the amount of renewable generation. The temporal shift in cooling demand, influenced by the thermal inertia of buildings, can extend from minutes to hours, or even longer when coupled with thermal storage systems, such as water tanks [5].

In this framework, reversible heat pumps play a significant role, as

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Nomenclature

Abbreviations

BUH	Back-up heater
DEH	Dehumidifier
STEPS	Stated Policies Scenario
HVAC	Heating Ventilation Air Conditioning
HP	Heat pump
HIL	Hardware in the Loop
GHI	Global Horizontal Irradiation
KPI	Key Performance Indicators
ML	Machine Learning
MPC	Model Predictive Control
Mac	Day selection approach based on energies
Clu	Day selection approach based on day clustering
Dur	Day selection approach based on durative curve/day
Typ	Day selection approach based on using a typical week with consecutives days only
REF	Reference control strategy without energy flexibility services
SCOP	Seasonal coefficient of performance
SC	Space Cooling
SL	Supervised learning
RBC	Ruled Based Controllers
RMSE	Root mean squared error
RL	Relative Humidity
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
STRAT	Energy flexible control strategy case

Symbols

A	Surface area (m^2)
c	Specific heat capacity (J/kg.K)
T	Temperature (°C)
Err	Error
D	Number of days (–)
$\dot{m}$	Mass flow rate (kg/s)
x	Absolute humidity (g/kg)
ρ	Mass density (kg/m^3)
SP	Spot prince (€/MWh)
f	Fraction
u	Control input
V	Ambient Volume
h_{fg}	Latent heat of vaporization of water (kJ/kg)

Subscripts

air	With reference to thermal properties of air
avg	average
corr	correction
elec	electrical
end	at the end
lat	latent load
max	Maximum
min	Minimum
Nom	At nominal conditions
Out	Outdoor air
Q1	First quartile
Q3	Third quartile
FullS	With reference to full summer period
7d	With reference to time shortened sequence of seven days
Sel	Amount that has to be selected
wat	With reference to thermal properties of water
vent	With reference to ventilation flow air
l	Number of construction layers within surface m, limited to the insulated building layer itself (–)
th	Thermal
i	Month
e	With reference to external conditions
a	With reference to internal conditions

their dynamic behaviour and control logic enable the effective exploitation of the energy flexibility, optimizing the interaction between the HVAC system, renewable energy sources, and the building environment. Conventional control strategies for heat pumps are typically based on fixed setpoints and predefined rules, relying on monitored variables values (i.e., Rule-Based Controllers, RBC) [6]. Advanced control strategies, such as Model Predictive Control (MPC), incorporates dynamic and adaptative strategies that utilise real-time data and are optimised using advanced algorithms [7]. However, their performance strongly depends on the accuracy to predict the building dynamic and in recent studies Machine Learning (ML) techniques have been increasingly applied to HVAC control [8]. While these approaches offer significant potential, they also require large high-quality datasets and involve greater computational resources, which may hinder their practical implementation, especially in real-time applications.

A first step in defining flexible HP control strategies is to have an accurate heat pump model that can capture short-term behaviour. In a comparative study, Evens and Arteconi [9] evaluated several modelling approaches for heat pumps. By means of a systematic increase in the complexity of the model, it was demonstrated that the majority of the effects become evident in the short-term behaviour. They developed and validated their short-term HP model within hardware-in-the-loop (HIL) experiments, which proved to be crucial for the testing of advanced control strategies and for identifying potential improvements under real operating conditions.

Since long-term experimental campaigns are time-consuming and costly [10], it is essential to design a short but representative test campaign to capture the most relevant operating conditions [11]. In this context, methodologies originally developed for annual energy system modelling were employed to reduce computational effort while preserving the representativeness of the underlying datasets. Typical days are usually extracted [12] or artificially constructed from full time series to preserve the key statistical and operational features of the original data. However, representative day approaches also introduce challenges related to concurrency and continuity. Concurrency is defined as the preservation of realistic correlations between events, such as the interaction between heating/cooling demand and variable renewable generation. Continuity is required to keep the building and storage devices' state of charge consistent from one time step to the next.

These challenges can be mitigated by the use of temporally consistent datasets, or by the selection of groups of consecutive days, which are effective in capturing temporal correlations and system dynamics [13]. Early applications focused on reducing annual datasets through a number of characteristic periods, such as peak-demand and off-peak demand periods in each season [14] or typical demand days for each month based on monthly average parameter values [15]. In both cases, the system operating conditions and energy demand follow similar patterns during the different seasons. However, the patterns are increasingly difficult to predict because of the growing penetration of variable renewable energy sources, which introduces greater irregularity in energy demand and supply prediction [16]. In order to overcome these limitations, several studies have proposed the application of cluster analysis to identify typical periods that can be repeated to approximate the annual cumulative curves. Ortiga et al. [17] proposed a graphical method for selecting a few typical days to represent annual cumulative heating and cooling demand curves. Domínguez-Muñoz et al. [18] applied a partitioning k-medoids method to reduce a full year of demand data, including power, heating and cooling profiles. Kotzur et al. [19] evaluated the efficiency of hierarchical clustering in estimating and optimizing the performance of a residential energy supply system and compared it to other partitional clustering approaches.

In the specific context of HP performance assessment, some studies have proposed selection criteria and guidelines to identify representative periods. Menegon et al. [11] applied a day clustering methodology [18] to heat pump testing, developing a short-term procedure for the dynamic characterisation of heating and cooling systems at component and system level. Their results highlighted the importance of incorporating dynamic behaviour in order to obtain realistic assessments of seasonal performance. In particular, clustering criteria based on outdoor air temperature (Tout) and global horizontal irradiation (GHI) yielded the closest agreement with annual simulation results. A further contribution comes from the MacSheep project [20], which developed a harmonised approach that integrates and extends existing heat pump testing methodologies. The proposed methodology aimed to standardise the unit under test by considering its physical boundaries, climatic conditions, load profiles, and distribution system. It then used six- and twelve-day representative test profiles to extrapolate the annual performance. An application of this methodology is presented in [21], where the performance of two different heating technologies is evaluated.

Evens et al. [22] proposed an alternative methodology to analyse the short-term behaviour and energy flexibility potential of heat pump systems. Unlike conventional time-aggregation approaches, this method prioritises the preservation of temporal continuity by selecting a representative week, thereby maintaining realistic temperature transitions.

Although much of the literature on representative period selection has investigated the dynamic behaviour of HPs, this has largely focused on the heating season. In particular, the typical period extraction proposed by Evens et al. [22] has been successfully tested under winter conditions; however, its effectiveness under summer conditions has yet to be assessed. Summer operation is particularly challenging due to higher variability in boundary conditions and the occurrence of pronounced peaks in electricity demand. This study addresses this gap by evaluating reversible heat pumps operating in space cooling mode under different flexibility scenarios, assessing whether the benefits of flexible control strategies, even when small, can also be captured through representative periods, and identifying which period-selection procedure can be recommended depending on the key performance indicators of interest.

A radiant floor cooling system was selected for the case study because of its higher thermal inertia. This makes it more challenging to evaluate electricity price-based control strategies since control actions produce more delayed effects on indoor conditions than in conventional air systems [23]. Therefore, an integrated simulation of the building and cooling system is required to evaluate these strategies. Thus, four methodologies are compared across three different climates under summer conditions: three are based on environmental variables, namely the typical period extraction method (Typ) introduced by Evens et al. [22], the clustering procedure (Clu) proposed by Menegon [11], and an aggregation technique employing environmental duration curves (Dur) [24], while the fourth is an energy-oriented method (Mac), developed within the MacSheep project [20] for the heating mode.

Several key performance indicators (KPIs) are used to evaluate how well each method reproduces the thermal, electrical, and comfort-related dynamics of the system. The ultimate objective is to provide the methodological insights needed for defining reliable, representative cooling cycles that will support experimental characterisation and the development of control strategies aimed at enhancing energy flexibility. Three different flexibility strategies are applied, taking into account the day-ahead electricity prices in Greece, Spain and Italy.

The paper is organized as follows: Section 2 provides an overview of the methodologies used to define representative day cycles. These include approaches originally developed for annual performance characterisation, day-aggregation procedures, and methods based on consecutive-day selection. It also describes the simulation models, boundary conditions, the system configuration, the set of energy-flexible control strategies and key performance indicators (KPIs) used in the analysis. Section 3 presents the representative cooling cycles identified by each methodology and compares their ability to reproduce the behaviour of a full summer simulation in terms of energy performance, costs, heat pump operation and thermal comfort. Section 4 discusses the results, highlighting the strengths and limitations of each approach and provides insights for future applications in experimental studies. Finally, Section 5 offers a concise summary of the primary conclusions and puts forward a series of overarching recommendations for evaluating energy flexibility in reversible heat pump systems.

2. Methods

This section describes the methodological framework used to define the representative day sequences and evaluate the energy flexibility of heat pumps (HPs) in space cooling applications.

2.1. Representative period selection and sequence length definition

Several approaches to identifying representative periods are proposed in the literature. Full annual datasets are typically condensed into shorter sequences of days or weeks for use in system studies, characterisation analysis or optimisation tasks. The selection criteria follow two alternative approaches [20]: 1) selection based on thermal and/or electrical energy-related metrics; 2) selection based on environmental variables. The present study applies four methodologies. One is an energy-oriented method (Mac), developed within the MacSheep project [20]. The remaining three rely on environmental conditions: a clustering procedure (Clu) proposed by Menegon [11]; an aggregation technique employing environmental duration curves (Dur) [24]; and the typical period extraction method (Typ) introduced by Evens et al. [22] extracts a representative winter or summer week to preserve the chronological sequence.

The definition of the sequence length represents an important methodological choice. Annual performance tests commonly employ sequences of six or twelve days; both approaches present limitations for systems characterised by high thermal inertia. Assigning a single representative day per month within a twelve-day sequence was found to be inadequate to capture system dynamics. Similarly, the six day sequence adopted in the MacSheep project [20] required a reduction in the thermal storage capacity to avoid energy overflow between consecutive days, which was considered unsuitable for the objectives of the present study. Accordingly, and in line with the findings of Evens et al. [22], this study adopts a seven-day period to assess the energy flexibility potential of HP system. This choice is further supported by the temporal structure of smart control strategies, which often follow weekly behavioural patterns, including differences between weekdays and weekends and scheduled variations in domestic hot water and space heating or cooling setpoints.

2.1.1. Selection based on energy demand profiles (Mac)

The methodology, developed within the MacSheep project [20], is energy based and thus requires a preliminary simulation to assess the daily thermal and electrical energy use. On the basis of the simulation results, it identifies the days in each month whose directly extrapolated energy use best represents the cumulative thermal and electrical energy demand for the full summer. The objective of the procedure is to minimise the discrepancy Err_{Mac} between the extrapolated daily energies and the cumulative seasonal demand:

$$Err_{Mac} = \sum_{i=1}^{n}\left(\left|E_{elec,avg,i} - \frac{D_i}{D_{sel,i}} \times \sum_{l=1}^{Dsel,i} E_{elec,l,i}\right| + \left|E_{th,avg,i} - \frac{Di}{Dsel,i} \times \sum_{l=1}^{Dsel,i} E_{th,l,i}\right|\right) \tag{1}$$

Where D_i denotes the number of days in month I and $D_{sel,i}$ is the number of days to be selected from month *i*. E_{th} and E_{elec}, represent the thermal and electrical energies, respectively, with the subscript *avg,i* indicating the average consumption within month *i*. In this study, the summer months from June to August are considered.

2.1.2. Selection based on environmental variables: clustering approach (Clu)

The selection of representative days is based on clustering methods that use environmental indicators (T_{out} and *GHI*). In the present study, the k-medoids algorithm is employed to categorise all summer days into seven clusters, and the corresponding medoids are extracted as representative days. The robustness of this clustering-based approach was confirmed by Menegon [11] through comparative tests in different climates (Bolzano, Zürich, Gdańsk, and Rome) and the deviation of the seasonal performance in heating mode remains below 5%, whereas in cooling mode it reaches values of around 30%. The higher deviation in cooling mode is primarily attributable to the discontinuous operation of the heat pump with brief and frequent activation periods. In such conditions, start-ups transients become of great significance, reducing the system's ability to achieve stable and optimal performance.

2.1.3. Selection based on environmental variables: duration curve approach (Dur)

An alternative approach of clustering methodologies based on temporal similarity is to implement a time-aggregation approach using duration curves, which preserves the distribution of real operating conditions. The method is employed to approximate the seasonal duration curves for two environmental variables (T_{out} and *GHI*) by selecting a limited number of representative days that reproduce the variability observed across the entire season. The approach, originally developed by Poncelet et al. [24] and previously applied to the winter conditions [22], is here applied to the summer season.

2.1.4. Selection based on environmental variables: typical week approach (Typ)

Evens et al. [22] proposed a selection strategy based on consecutive days, ensuring realistic environmental transitions between representative days. As with the Clu and Dur approach, the daily average outdoor temperature (T_{out}) and the daily sum of global horizontal irradiance (*GHI*) are considered, and both are normalised in order to provide equal weighting. The method identifies a sequence of seven consecutive days (7d) that minimises the combined root mean squared error (RMSE) between the 7d averages of T_{out} and *GHI* and the corresponding values for the full summer period (FullS):

$$RMSE = \sqrt{\left(T_{out,7d} - T_{out,FullS}\right)^2 + \left(GHI_{7d} - GHI_{FullS}\right)^2} \tag{2}$$

Equal weighting of temperature and irradiance is used in Eq. (2), which provided sufficient results during the winter months. However, summer conditions usually involve greater influence of irradiance influence on the building dynamics and on the cooling load. Thus, a preliminary analysis was carried out, increasing the weighting factor of GHI by 150 and 200%. The same typical week is selected, indicating that the method is robust with respect to the relative weighting of both environmental variables, even under summer conditions.

2.1.5. Construction and ordering criteria of representative days

The selection of representative days involves other two key considerations: the ordering of the selected day and the definition of an initialization day. Once the days have been selected, their order must ensure thermally coherent transitions. A range of strategies have been advanced in the extant literature, including the maintenance of their chronological position in the year [25], sorting them by increasing or decreasing daily mean outdoor temperature, or imposing predefined sequences such as warm–cold–warm to reduce the temperature difference between the first and last day of the cycle [26]. Smoothing functions have also been explored to reduce residual temperature discontinuities between non-consecutive days, although preliminary tests showed limited benefit [27,28]. Building on the methodology developed by Evens et al. [22], the present study reorders non-consecutive approaches (Mac, Dur, and Clu) by minimizing the temperature difference between the end $T_{out,end,l}$ and the start $T_{out,start,l+1}$ of each day, as expressed in Eq. (3), in order to achieve the smoothest possible transitions.

$$Err = min\sqrt{\sum_{l=1}^{Dsel-1}\frac{\left(T_{out,start,l+1} - T_{out,end,l}\right)^2}{D_{sel} - 1}} \tag{3}$$

Finally, an additional initialization day is included to stabilise system temperatures and limit variations in the building's thermal state of charge between the start and end of the test period. For the Typ (consecutive) method, it is taken as the day immediately preceding the selected week in the weather file, preserving full consecutiveness. For Mac, Dur, and Clu (non-consecutive) methods, it corresponds to the last day of the constructed representative week.

2.2. Case study: cooling operation

The case study focuses on a two-floor detached residential building with a total floor area of approximately 194 m^2, equipped with underfloor terminals. The present study extends a previously developed and experimentally validated Modelica [29] model of the residential heat pump system [9], originally designed for space heating. The model has been modified to simulate performance in cooling operation. The underfloor terminals are supplied with by a reversible Daikin EGSAX06D9W unit with a nominal cooling capacity of 3.6 kW and electrical power of 0.43 kW at nominal conditions (LWC 18 °C, EBT 15 °C). The heat pump operation in cooling mode is given by the implementation of cooling performance maps from the manufacturer [30]. On the source side, the ground-coupled system is represented with a fixed inlet brine temperature of 20 °C. On the demand side, the underfloor terminals are supplied by chilled water at a nominal temperature of 18 °C, which is dynamically adjusted via a climatic compensation function (described later) while maintaining a fixed 5 K supply-return temperature. A small inertia storage of 25 l has been incorporated, as recommended by the heat pump manufacturer. The schematic of the system is shown in Fig. 1. The building and cooling system ware modelled in Modelica [29], and the simulations are carried out utilising a 60-s time step.

2.2.1. Integration of dehumidification

In order to ensure compliance with thermal comfort requirements and to address the critical issue of humidity control in radiant cooling systems, particularly the prevention of surface condensation, a dedicated dehumidification model is developed and integrated into the simulation framework. The adopted dehumidifier from the IDEAS library [29], allows the removal of moisture from the air stream as in Eq. (4):

$$\dot{m}_{wat} = u \bullet \dot{m}_{wat,nom} \tag{4}$$

where $\dot{m}_{wat}$ is the water mass flow rate removed from the air stream, and $\dot{m}_{wat,nom}$, is the nominal mass flow rate parameter and u is the control input, which is iteratively modified in order to satisfy the moisture

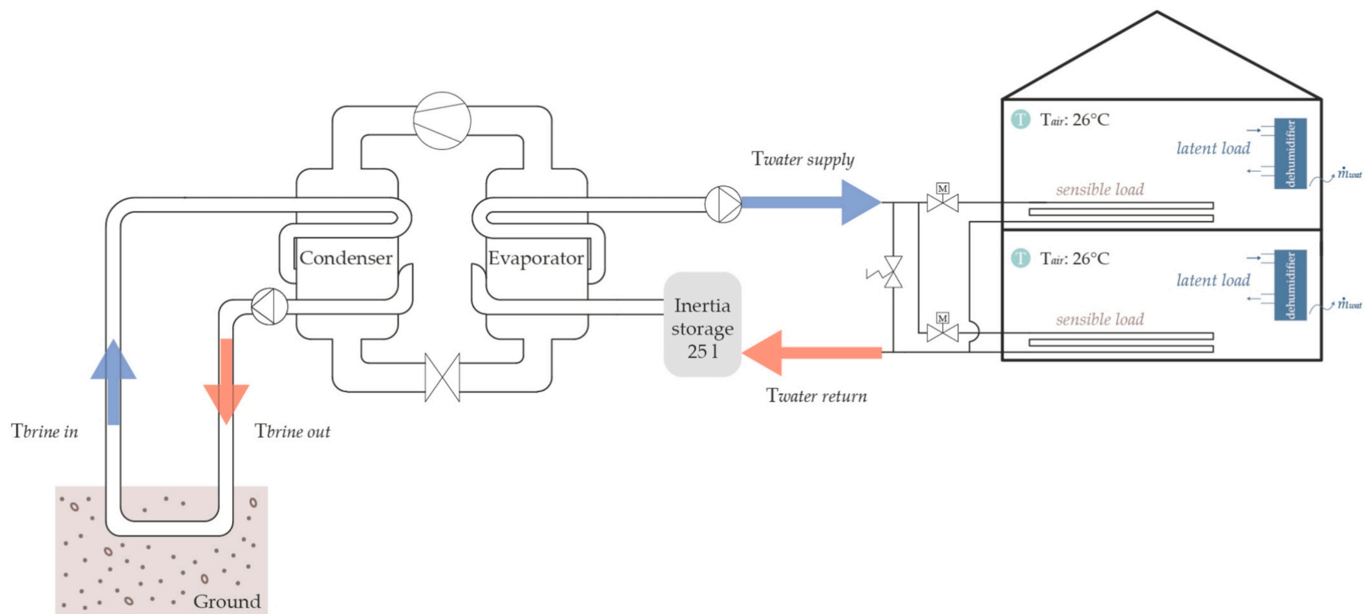

Fig. 1. Schematic representation of the ground-coupled reversible heat pump and underfloor cooling system.

balance on the internal air, i.e.

$$\rho_a V \frac{\partial x_a}{\partial \vartheta} = \dot{m}_{vent} \bullet (x_e - x_a) + \dot{m}_{wat} \tag{5}$$

where x_e, x_a is the humidity ratio at external and internal respectively, ρ_a is the air density, V is the ambient volume and $\dot{m}_{vent}$ is the ventilation flow air. In this study, the air dehumidifier operates exclusively in dehumidification mode, thus $\dot{m}_{wat}$ is always negative. Based on the simulated moisture removal rate, the thermal energy load associated with the dehumidification process is quantified assuming a constat latent heat h_{fg} equal to 2570 kJ/kg. The corresponding electrical energy demand of the dehumidifier is estimated, as defined in Eq. (6) taking into account the coefficient of performance (COP) of the device, as provided in the manufacturer's technical datasheet [31].

$$E_{elec,DEH} = \frac{\dot{m}_{wat} * h_{fg}}{COP_{DEH}} \tag{6}$$

2.3. Flexibility characterisation

Energy flexibility in space-cooling applications is assessed through a comparative analysis conducted within a comprehensive simulation environment, enabling general conclusions on the definition and requirements of representative cycles. As shown in Fig. 2, the study's framework included three climatic locations representative of Southern Europe, four distinct representative day selection methods, and a total of three control strategies.

The climatic locations are selected to represent at least two climate types, according to the Köppen–Geiger classification (Csa and Bwh). The same heat pump size is adopted for all climates and is chosen to ensure

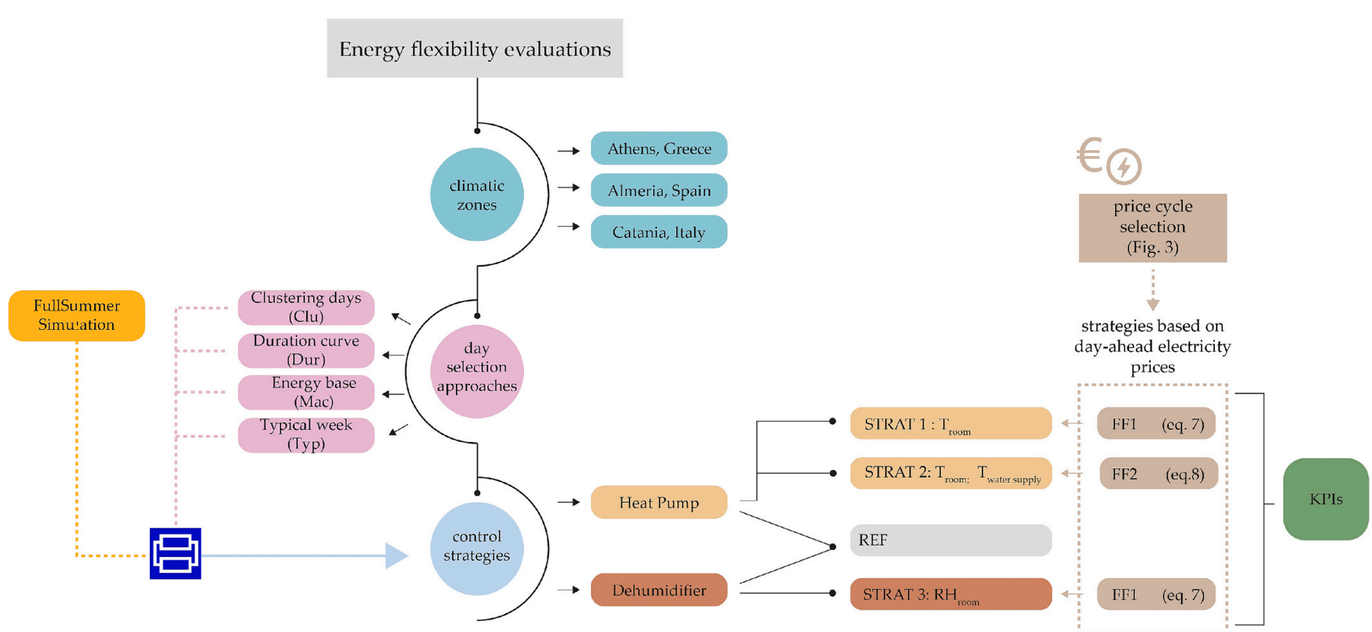

Fig. 2. Overview of the comparative study for energy flexibility evaluations.

Table 1
Dynamic tariff characteristics of the full summer and the representative cycle for Greece, Italy and Spain.

	FullS Greece	Selected short sequence Greece	FullS Spain	Selected short sequence Spain	FullS Italy	Selected short sequence Italy
Minimum [€/MWh]	0.04	0.04	−2.00	0.00	9.65	85.97
First quartile [€/MWh]	88.52	90.62	41.26	40.00	101.46	103.13
Second quartile (median) [€/MWh]	105.58	108.61	82.00	75.75	110.95	108.04
Third quartile [€/MWh]	128.41	126.39	106.37	100.92	122.86	119.89
Maximum [€/MWh]	850.00	362.91	175.55	137.18	250.00	178.48
Average [€/MWh]	121.56	116.09	73.47	69.98	114.81	114.60
Average deviation [€/MWh]	47.13	42.74	34.32	30.53	17.29	13.95

acceptable operation in every case. Specifically, the heat pump achieves on-time percentages consistently above 58% across the simulated scenarios, thereby ensuring sufficiently demanding climatic conditions for assess summer performance. Based on these criteria, Catania, Italy (Csa), Almeria, Spain (Bwh) and Athens, Greece (Csa) are selected.

2.3.1. Energy flexibility services

The present study primarily considers a demand response flexible control strategy based on day-ahead electricity prices. In order to facilitate an analysis of the interaction between the control strategy input and actual control actions, the period representative of the volatility and spread of the electricity prices for the full summer is required [32]. Statistical indicators, including minimum and maximum prices, quartile ranges, and average deviation, are analysed. The period whose average deviation and price difference between the first and third quartiles most closely matched those of the full summer is then extracted. This ensures that the dynamic price trend and HP response in the test sequence reflect the behaviour of the entire summer period. Table 1 shows the statistical values and Fig. 3 shows the differences between the full summer price data and the selected representative price sequence. As an example, in Greece the average deviation is the 47.13 €/MWh for the full summer period and 42.74 €/MWh for the representative period. It should be emphasized that Greece is the country with the greatest price variability as shown in Table 1 and is therefore most suited to the application of flexibility strategies based on day-ahead electricity prices. The potential cost reductions mentioned within this study only refer to the variable costs influenced by spot electricity prices. Fixed charges, grid operator fees, taxes and other levies are deliberately excluded, as the analysis focuses exclusively on the dynamic component of the electricity bill.

2.3.2. Application of control strategies

Flexible control strategies are evaluated to derive general recommendation for the representative day selection procedure. Table 2 summarizes the investigated cases, including the reference control without energy flexibility services (REF).

In cases STRAT1 e STRAT2, control strategy adjust the room-thermostat setpoint and the space-cooling (SC) supply temperature, thereby indirectly modulating the HP operation (see Fig. 2). They employ a different definition of the dimensionless flexibility factor (*FF*), which determines the magnitude of the setpoint adjustment in response to changes in electricity prices. The setpoint control rules are given in Table 2 and the dimensionless flexibility factors are defined in Eq. (7) and Eq. (8), where the momentary, minimum, maximum, average, first quartile and third quartile spot prices for each day are denoted by SP, SP_{min}, SP_{max}, SP_{avg}, SP_{Q1}, SP_{Q3} respectively.

$$FF1 = \begin{cases} If\ SP \geq SP_{avg}; \dfrac{SP - SP_{avg}}{SP_{max} - SP_{avg}} \\ If\ SP < SP_{avg}; \dfrac{SP - SP_{avg}}{SP_{avg} - SP_{min}} \end{cases} \tag{7}$$

$$FF2 = \left(\max\left(\min\left(\frac{SP - SP_{Q1}}{SP_{Q3} - SP_{Q1}}; 1 \right); 0 \right) \bullet 2 \right) - 1 \tag{8}$$

STRAT1 uses dimensionless flexibility *FF*1 based on the relative difference from average, the minimum and maximum daily prices (Eq. 7); STRAT2 uses dimensionless flexibility *FF*2 where only the first and third daily electricity price quartiles are adopted (Eq. 8).

Compared with FF1, which is based on the minimum and maximum daily prices, FF2 provides a faster response to electricity price variations. Furthermore, in STRAT2 the room thermostat is deliberately shifted to either on-mode or off-mode using an additional control, referred to as "Shift room thermostat mode" in Table 2. In contrast to the conventional thermostat adopted in REF e STRAT1, which changes its operating state only after the temperature exceeds the setpoint plus or minus the predefined hysteresis (dead band), STRAT2 can temporarily bypass the thermostat logic and briefly forced it into a predefined operating state

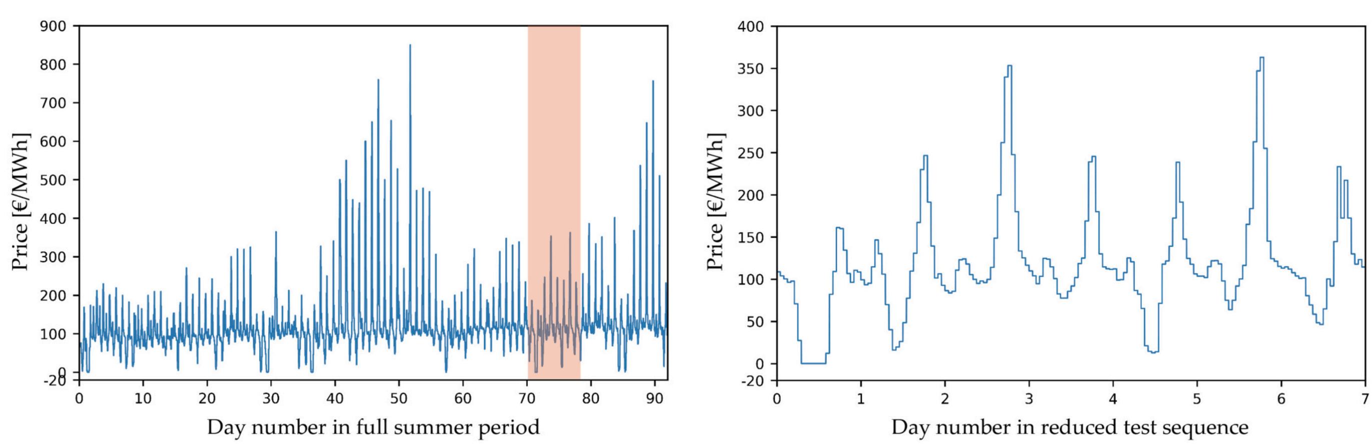

Fig. 3. Greece dynamic tariff graphical comparison of full summer period and representative cycle. The extracted period for the reduced test sequence is also highlighted in the full summer period.

Table 2
Overview of investigated cases.

Characteristic	REF	STRAT1	STRAT2	STRAT3
Setpoint T_{room}	25 °C	25 °C + 0.75 · FF1*	25 °C + 0.25 · FF2**	25 °C
Hysteresis T_{room}	±0.50	±0.25	±0.25	±0.50
Shift room thermostat mode	N.A.	N.A.	If setpoint T_{room}; Increases: shift to off-mode Decreases: shift to on-mode	
SC supply temperature	SC cooling curve	SC cooling curve, adjusted by new T_{room} setpoint via Eq. (9)	SC cooling curve +1.5 · FF2**	SC cooling curve
Humidity control band	50%	50%	50%	50% + 0.2 · FF1* In range 45–70%

* price-based factor FF1, Eq. (7); ** price-based factor FF2, Eq. (8).

(on-mode or off-mode) for one second. This short intervention is sufficient to trigger a change in the heat pump operating mode. After the forcing signal is removed, the thermostat resumes normal operation. If the measured indoor temperature remains within the admissible hysteresis band, the newly enforced operating state is maintained. Otherwise, the thermostat autonomously reverts to its original operating mode in order to preserve indoor thermal comfort, thus disregarding the flexibility request. The specific setting in Table 2 were selected through successive adjustments based on the full-summer simulation, in order to ensure compliance with the comfort limits.

As concerns to the SC supply temperature, it is controlled according to the following cooling curve:

$$T_{SC,sup,i} = T_{room,i} - \left(max\left(0; \frac{T_{out,i} - T_{room,i}}{T_{out,Nom} - T_{room,REF}}\right)\right) \bullet \left(T_{room,REF} - T_{SC,sup,Nom}\right) \tag{9}$$

$T_{SC,sup,i}$ represents the supply temperature setpoint for space cooling at hour *i*; $T_{SC,sup,Nom}$ denotes the supply temperature setpoint for space cooling at nominal conditions; $T_{out,i}$ and $T_{out,Nom}$ correspond to the outdoor air temperature at hour *i* and under nominal conditions; $T_{room,i}$ is the indoor air temperature setpoint at hour *i*.

In the REF case $T_{room,i}$ is constant and equal to $T_{room,REF}$, whereas in STRAT1 it is given by the setpoint control rule. In STRAT2, the SC cooling curve takes into account a correction given by factor FF2 as described in Table 2. Therefore, STRAT2 integrates both the control strategy modification and control setting adjustment.

In STRAT1 and STRAT2 the indoor relative humidity (RH) is kept constant at 50%. By contrast, STRAT3 maintains a constant room temperature setpoint and controls the stand-alone dehumidification system through price-based modulation of the RH setpoint. The modulation is given by the dimensionless flexibility factor *FF1* (see Table 2) and constrained within 45%–70% RH to preserve indoor comfort and avoid condensation risk on radiant floor. Higher prices ($FF1 > 0$) increase RH setpoint, whereas lower prices ($FF1 < 0$) trigger stronger dehumidification.

2.4. Energy flexibility performance indicators

Key Performance Indicators (KPIs) provide a quantitative methodology for evaluating the effectiveness of control strategies and for comparing their performance against the reference model. Selecting a pertinent set of KPIs ensures that the assessment is both objective and aligned with the evaluation requirements. Even if KPI definitions remains strongly case-study oriented [33,34], three primary domains consistently emerge: energy consumption, occupants' thermal comfort and energy cost. Additional metrics, such as flexibility potential, exergy efficiency, photovoltaic self-consumption and CO_2 emissions, are occasionally included, reflecting the increasing multidimensionality of energy flexibility assessment. Table 3 provides an overview of the KPI selected for this study within four main categories: energy performance, heat pump operation, energy cost, and thermal comfort.

In order to evaluate the energy flexibility of the model under dynamic pricing strategies, both absolute indicators (e.g. costs in euros, energy consumption in kWh) and relative variations with respect to the reference case are considered. Absolute indicators provide a direct measure, while relative variations are particularly valuable when comparing flexible control strategies.

Furthermore, to provide insight into how energy use is distributed between low- and high-price periods, daily electricity consumption is allocated to eight price intervals and normalised by the total daily consumption. For each interval, cumulative consumption is calculated across all simulated days (excluding the initialization one) and expressed as a percentage of total consumption. An Energy Shift indicator is then derived, ranging from 0%, when the heat pump operates exclusively during the lowest price interval, to 100% when it operates solely in the highest one. This normalised metric enables comparison across scenarios by capturing both price-flexibility exploitation and the resulting consumption distribution.

The representative-day selection methods (Mac, Dur, Typ, Clu) are assessed by computing the root mean square error (RMSE) between KPIs values obtained from the representative day sequence (7d) and those obtained over the full summer period (FullS). The index *i* represents the evaluated flexible strategy, denoted by *STRATi*, out of a total of the two control strategies. The RMSE is expressed as a percentage due to the relative comparison to the reference case without flexibility services, denoted by REF. This indicates how accurately each representative cycle reproduces the full-period performance across the two control strategies modulating the HP operation.

$$RMSE = 100 \bullet \sqrt{\frac{\sum_{I=1}^{2}\left(\frac{KPI7d,STRATi - KPI7d,REF}{KPI7d,REF} - \frac{KPIfullS,STRATi - KPIFullS,REF}{KPIfullS,REF}\right)^2}{2}} \tag{10}$$

A set of KPIs related to latent load fraction, dehumidifier cost savings and thermal comfort is included in the analysis. The comfort indicator is defined as the number of hours in the considered period when the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied

Table 3
Key performance indicator for the evaluation of the control strategies.

Energy performance	Heat pump operation	Energy cost	Thermal comfort
• Electricity consumption • Remaining energy shifting potential • SCOP • Latent load fraction	• Number of compressor cycles • Average compressor modulation	• Billing cost • Cost reduction of the dehumidifier	• PMV • PPD

(PPD) [34] satisfy the following condition:

$$Comfort = \text{number of hours } (|PMV| < 0.5\,; PPD < 10\%) \quad (11)$$

Thus, the $Reduc_{comf}$ indicator, as defined in Eq. (12), is introduced to quantify the percentage deviation in comfort between the flexibility strategies and the reference case. A value equal to 0% indicates that comfort is preserved, negative values denote a reduction in comfort, and positive values would reflect an improvement.

$$Reduc_{comf} = \frac{Comfort_{STRAT\ i} - Comfort_{REF}}{Comfort_{REF}} \times 100\%. \quad (12)$$

3. Results

3.1. Environmental data analysis

This section presents the weeks identified by the different period selection methods and compares them to the full summer in terms of outdoor temperature and solar irradiance. Fig. 4, Fig. 5 and Fig. 6 present a comparison of four different period selection methods (Typ, Clu, Mac, Dur) compared to the full summer period (FullS) for three mediterranean countries: Greece (Athens), Spain (Almeria) and Italy (Catania). For each climate case, the results are organized into three visual components. Panel (a) presents a scatter plot of the daily sum of global horizontal irradiation (GHI) against the daily average outdoor temperature (T_{out}) for the different selection methods. Panel (b) shows a boxplot of the daily average outdoor temperature and panel (c) reports a boxplot of the daily sum of GHI by method.

In the case of Greece, the full summer dataset includes a wide range of outdoor temperatures (18–32 °C) combined with consistently high solar radiation levels (3–8.5 kWh/m^2·day). Days selected by Typ method concentrate around average conditions; the Dur and Mac methods demonstrate greater coverage of extremes. A similar trend is shown in Spain.

Italy climate exhibits lower maximum temperatures (up to 28 °C) and slightly lower solar radiation than the other two countries. Nevertheless, Clu and Dur stand out for capturing broader global horizontal irradiation fluctuations, suggesting their enhanced ability to represent solar variability.

When considered across all climates, Typ method is characterised by a concentrated distribution of data points, supporting previous findings [22] that it typically captures a mild representative week with limited variability in environmental conditions, thereby minimizing variability but also underrepresenting extremes. Clu and Dur perform more robustly in preserving variability, particularly in Spain and Italy. The Mac approach preserves in general a higher variability in the mean hourly temperature profiles than in the global horizontal irradiation.

As illustrated in Table 4, the relative strengths and weaknesses of each approach are highlighted. The Typ approach provides intermediate accuracy, with an RMSE value (Eq.2) ranging from 3.70% (Spain) to 5.45% (Greece). The Clu approach demonstrated the most consistent and balanced performance across climates, with RMSE values ranging from 2.43% (Greece) to 3.00% (Spain). The Mac approach achieved the lowest RMSE in Spain (1.82%) and generally performed well across the countries. Although the Dur approach can capture a wide range of variability, as reflected in the distribution shown in the boxplots, it fails to capture the average conditions, resulting in errors of up to 13.64% in Italy.

The obtained results demonstrate that both the Mac and Clu approaches are effective in reproducing the full period behaviour, with Clu exhibiting greater robustness across climates, while Typ is robust in reproducing average climatic conditions. Conversely, Dur tends to overestimate deviations.

3.2. Energy flexible control strategies

This section provides a comparative analysis of the different representative-day selection approaches, evaluating their capability to reproduce the outcomes of the full summer simulation. Moreover, the analysis investigates the effectiveness of each method in capturing the system's energy flexibility under the different control strategies, as illustrated in Fig. 7. The evaluation does not depend exclusively on the numerical proximity to the full summer results, but also on the ability to preserve the characteristic trend between the strategies.

The results have been organized according to the KPI. For each indicator, both the absolute values and the relative variation from the full summer simulation are reported. This enables a comprehensive assessment of the methods in terms of accuracy and behavioural consistency.

When analysing the *remaining energy shift* KPI, a reduction in this indicator reflects an improvement in demand flexibility, as it results from a larger fraction of total electricity consumption being shifted towards low-price hours. This behaviour indicates the effectiveness of the adopted strategy, which should be able to anticipate or delay the cooling load according to dynamic electricity pricing. In the context of the selection methods employed, Mac consistently exhibits minimal numerical deviations, mainly in Greek and Italian climates. A similar result is obtained by Clu, which is numerically aligned to the full season but favours STRAT2 (lower value) in both Greek and Italian climates when comparing relative values. By contrast, Typ shows a good alignment in the absolute values and consistently preserves the characteristic trend in both relative and absolute values across the three climates. Nonetheless, it tends to slightly overestimate the flexibility improvement, predicting a more favourable shifting behaviour than observed in the full-season simulation particularly under STRAT1 in the Italian climate. Finally, Dur generates larger reductions, particularly in Greece and Spain, suggesting that it may overestimate the system's demand-shifting potential and predict a stronger redistribution of the electrical load towards low-price hours than is observed in the full-season simulation.

Regarding the *electricity cost of the heat pump*, STRAT1 and STRAT2 are equivalently effective. In Greek case, STRAT1 reduces the cost by

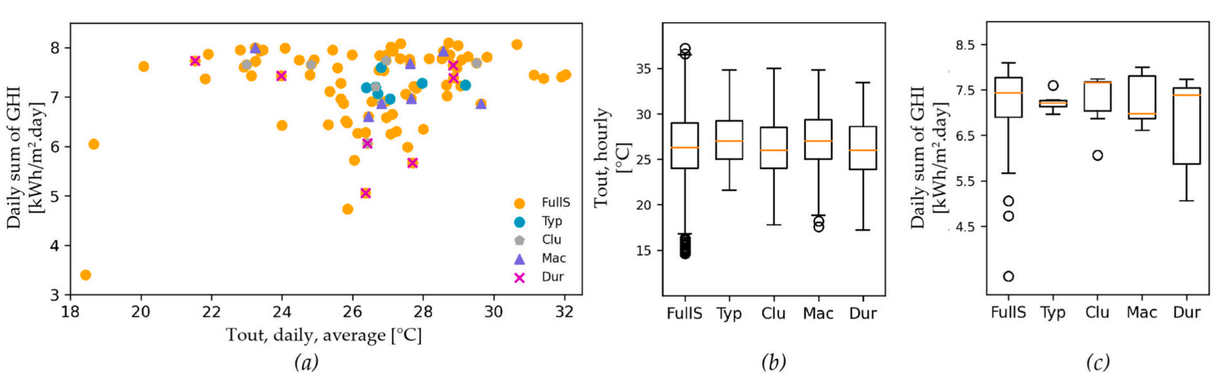

Fig. 4. Comparison of day selection for Greece (a) spread of (Tout-GHI) (b) boxplot of hourly variation of Tout and (c) boxplot of daily sum of GHI.

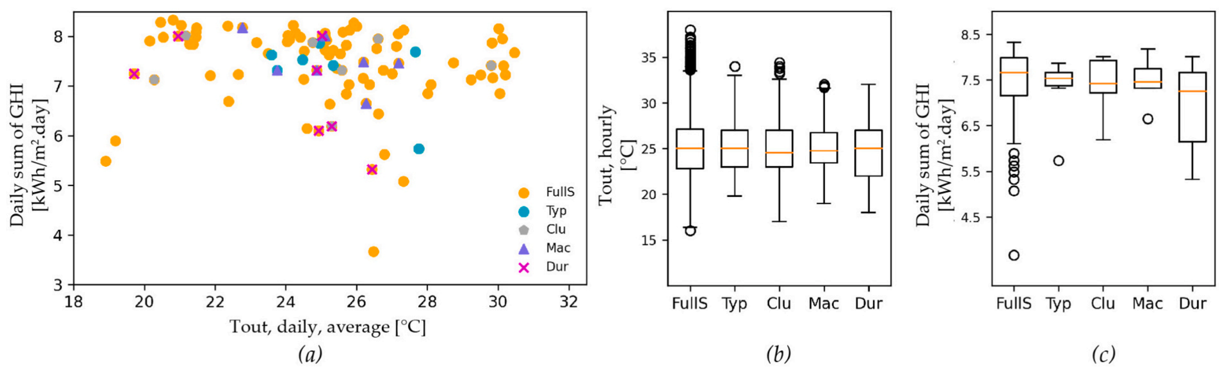

Fig. 5. Comparison of day selection for Spain (a) spread of (Tout-GHI) (b) boxplot of hourly variation of Tout and (c) boxplot of daily sum of GHI.

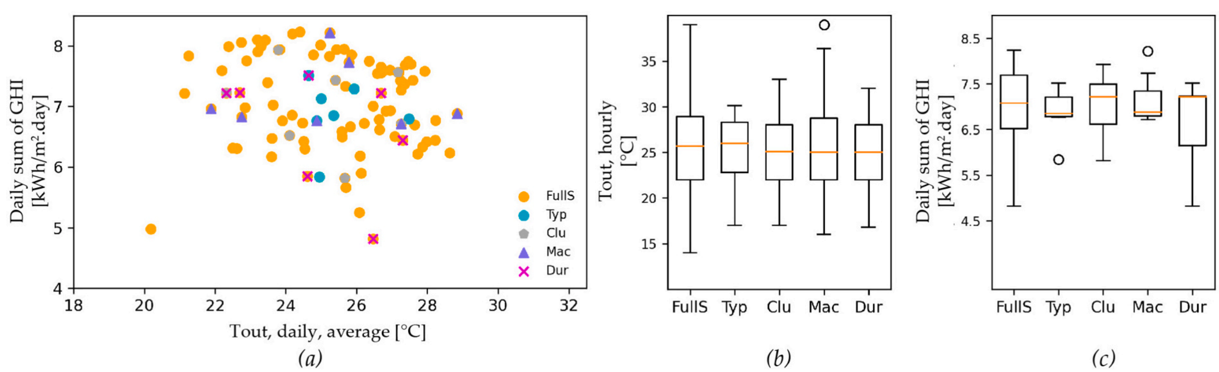

Fig. 6. Comparison of day selection for Italy (a) spread of (Tout-GHI) (b) boxplot of hourly variation of Tout and (c) boxplot of daily sum of GHI.

Table 4
Comparison of key environmental indicators (T_out average, average GHI daily sum) between seven-day representative cycle selection methods and the full summer period, RMSE (Eq. 2).

Approach	Greece	Spain	Italy
Mac [°C, kWh/m^2.day]	(27.14; 7,27)	(25.16; 7,49)	(25.23; 7,16)
Clu [°C, kWh/m^2.day]	(26.30; 7,27)	(25.35; 7,31)	(25.09; 7,03)
Dur [°C, kWh/m^2.day]	(26.23; 6,71)	(24.73; 6,90)	(24.96; 6,62)
Typ [°C, kWh/m^2.day]	(27.15; 7,22)	(24.78; 7,42)	(25.46; 6,89)
FullS [°C, kWh/m^2.day]	(26.55; 7,19)	(25.13; 7,41)	(25.32; 7,06)
RMSE Mac [%]	4.65	1.82	3.11
RMSE Clu [%]	2.43	3.00	2.70
RMSE Dur [%]	10.45	1.69	13.64
RMSE Typ [%]	5.45	3.70	4.49

−16.18% and STRAT2 by −13.69%; in Spanish case STRAT1 reduces the cost by −13.14% and STRAT2 by −10.41%. Conversely, in Italian Climate, the very low electricity price variation (see Table 1) causes absolutely negligible reductions and makes this case less relevant in determining the method that best represents the full summer.

In the comparison between the representative days and the full summer, all selection methods predict lower cost values compared to the full summer simulation. Among them, Dur exhibits the most significant deviations in all climates, particularly in Greece. Mac provides a good representation of the relative variation in Italy and Spain, though in the latter it underestimates the most the absolute electricity. Typ performs well in the Greek climate; it significantly overestimates the relative cost reductions in Spain, but to a lesser extent than other methods. Considering the relative change in cost, Clu emerges as the most stable approach across climates. However, when the Italian case is given less weight due to the flat electricity prices, Typ shows the best results in terms of preserving trends and absolute values.

Regarding the *electricity consumption*, Clu aligns closely with the FullS results when considering the relative differences. Nevertheless, in terms of absolute values, it tends to underestimate the total electricity consumption. Typ captures the overall trends observed in Greece and Spain, and it once again provides the most accurate estimate in absolute terms. In Italy, it fails to reproduce the trend from STRAT1 to STRAT2. With Mac, though, it is the method which underestimates the total electricity by the least. In Spain, Mac shows a substantial deviation from the REF scenario to both STRAT1 and STRAT2, which are nearly double that of the reference model. Dur, on the other hand, consistently exhibits the most extreme underestimations across all climates and strategies.

Fig. 8 presents the root mean square error RMSE values (Eq. 10) for several key performance indicators (KPIs) relevant to the energy flexibility analysis. The evaluation of the four methods (Typ, Mac, Clu and Dur) across Greece, Spain and Italy reveals clear differences in accuracy and robustness. The RMSE of the energy shift is comparable for Mac and Clu, with errors generally falling below 10% across all climates. It is notable that in Greece, Mac achieves a markedly better performance, with an RMSE close to 2%, while Clu maintains values around 8%, which are comparable to Typ in this specific climate. With regard to the cost of electricity, both Mac and Clu consistently achieve RMSE values below 2% in Italy, between 3% and 7% in Spain, while in Greece Clu and Typ remain below 8%. The SCOP indicator further corroborates the robust performance of Mac and Clu. In Spain, both methods remain below 1%, whereas in Italy, Clu and Dur attains this level of accuracy. In Greece, Typ, Mac and Clu all demonstrate RMSE values of less than 2%. Finally, for the heat pump electricity consumption, RMSE values below 2% are obtained by Mac and Clu in Italy, and by Clu in Spain, while in Greece Mac, Typ and Clu all remain below this threshold. In both Spain and Italy, Typ also maintains RMSE values below 5%.

The KPIs directly related to the operation of the heat pump, such as *average compressor modulation* and *compressor cycles*, show high RMSE values are observed across all methods and climates. These values are higher than those observed during the heating season [22], confirming

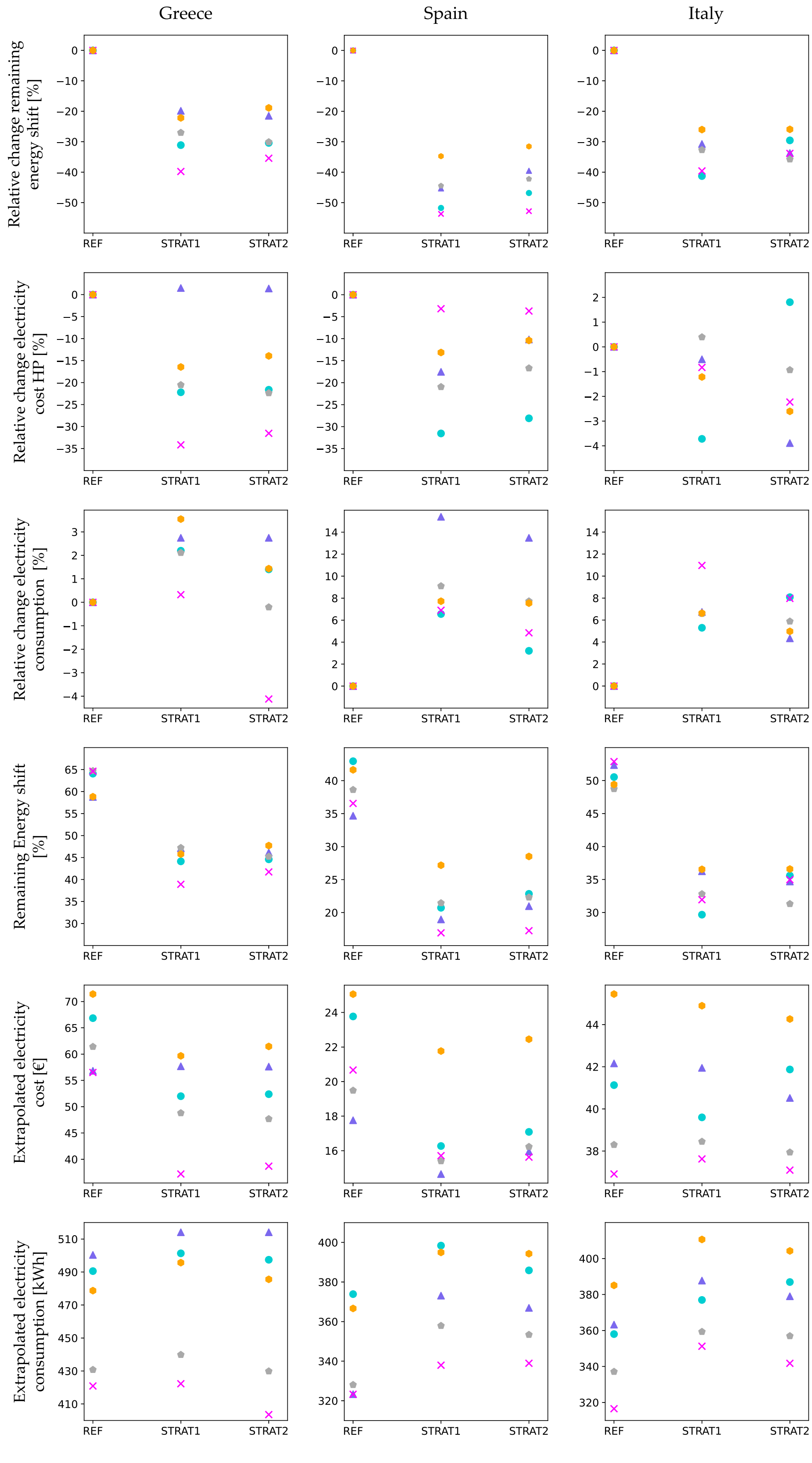

Fig. 7. Comparison of the energy flexibility KPIs across the three analysed climates (Greece, Spain, and Italy).

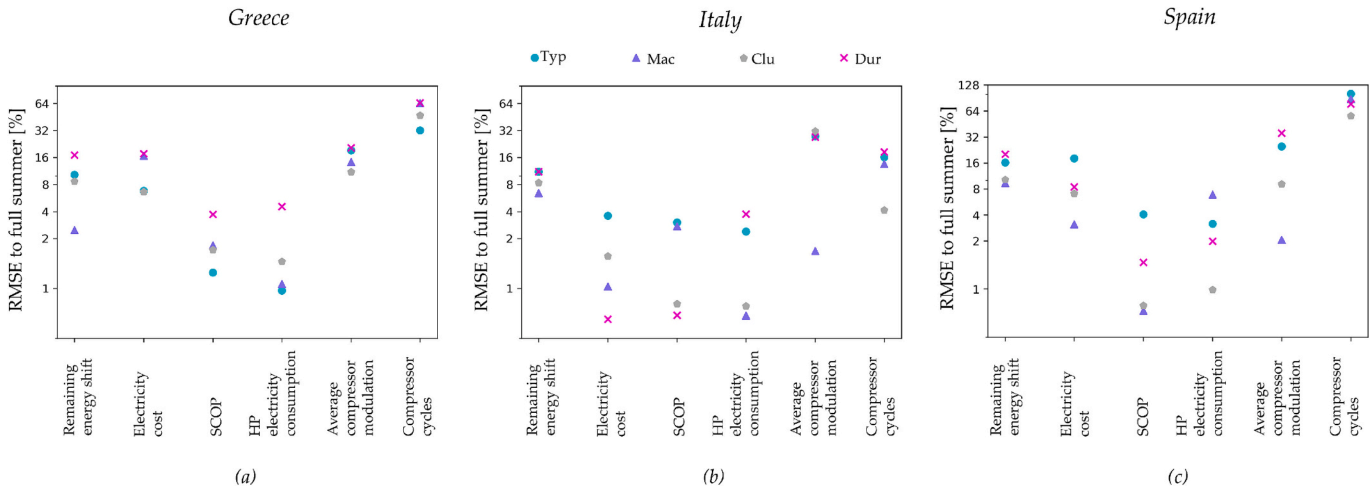

Fig. 8. RMSE of KPIs compared to full summer simulation for Greece, Italy and Spain.

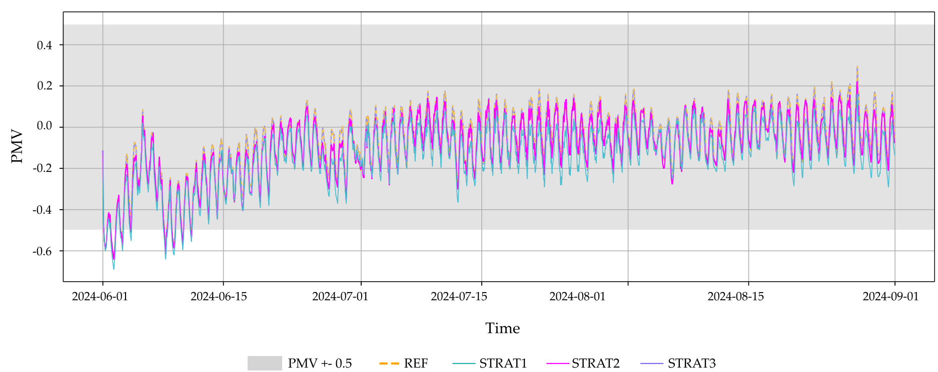

Fig. 9. Thermal comfort full summer simulation - Greece.

the greater difficulty in defining a representative week in cooling mode [11] and in capturing the transient behaviour of the reversible heat pump.

3.3. Dehumidification strategy

The electricity cost performance KPI in the previous paragraph (Fig. 7–8) does not include the electricity consumption associated with maintaining the relative humidity setpoint, as it is set at 50% for all the compared cases (REF, STRAT1 and STRAT2).

As in the reference case, without flexibility (REF), the seasonal latent load represents 27% of the total thermal load in Greece, it reaches 40% in Italy and the 46% in Spain, it is interesting to evaluate a dehumidification-dedicated control strategy. In fact, implementing STRAT3 over the full summer period reduces the electrical demand of the dehumidifier $E_{el,DEH}$ (Eq. 6) by 1.6% in the Italian climate, 4.1% in the Spanish climate and up to 8.2% in the Greek climate.

As concern the accuracy of the representative-day selection methods with respect to the FullS simulation, the absolute error of the latent load fraction and the cost-saving KPIs are computed by comparing each representative approach against the full summer simulation. The results are reported in Table 5.

Regarding the *latent load fraction* (f_{lat}), the Typ method consistently shows the lowest deviations, with absolute errors generally below 5–6% across all climate zones. The Mac method also performs satisfactorily, although for the Spanish climate the error exceeds 10%. In contrast, the Clu and Dur methods introduce more pronounced and systematic deviations, particularly evident in all climates for the Dur approach. Regarding the economic performance, *cost saving*, the absolute error of the representative day methods in giving less than 10% across the different climates. Typ shows the best performance in Greece and Spain; whereas its error increases in Italy. Overall, the Typ approach demonstrate a good performance.

3.4. Evaluation of thermal comfort

An assessment of comfort and discomfort hours is carried out across all control strategies and representative methods to evaluate indoor thermal comfort conditions. As illustrated in Fig. 9, in the Greek climate, the adoption of alternative control methodologies does not affect the overall comfort levels with the PMV following the same trend as observed in the reference case. In all cases, a limited number of comfort

Table 5
Absolute error of representative weeks relative to the Full Summer for STRAT3: latent load fraction and dehumidifier cost-saving prediction.

		GREECE				SPAIN				ITALY			
[%]	KPI	*Typ*	*Mac*	*Clu*	*Dur*	*Typ*	*Mac*	*Clu*	*Dur*	*Typ*	*Mac*	*Clu*	*Dur*
ERROR	f_{lat}	1.1%	4.6%	4.0%	21.1%	5%	13.4%	17.2%	12.5%	5.8%	6.1%	11.8%	12.9%
	Cost saving	0.9%	6.6%	3.4%	9.4%	2.7%	0.9%	4.9%	6.4%	7.2%	9.7%	3.7%	3.3%

violations (PMV outside the ±0.5 range) is observed at the beginning of June, when the cooling system is switched off, but the indoor temperature is lowered by the natural ventilation in presence of a relatively low outdoor temperature. Therefore, the introduction of flexibility-oriented control approaches does not systematically deteriorate thermal comfort conditions.

Focusing on the Greek climate, the comfort hours reduce by 0.75% for STRAT1 with respect to REF case. START2 e STRAT3 exhibit lower and identical comfort level reduction, 0.24%. Nevertheless, notable differences emerge in terms of economic performance: while STRAT2 yields a marginal cost reduction of 0.4% compared to the reference case, STRAT3 achieves an 8% cost reduction. Analogous consideration can be carried out for the Spanish climate, where the comfort hours reduce by 3.25% in STRAT1, 1.71% and 0.06% in STRAT2 and STRAT3 respectively. Finaly in the Italian climate, the comfort hours reduce by 1.66% in STRAT1, 0.9% and 0.3% in STRAT2 and STRAT3 respectively.

Among the flexibility-oriented strategies, STRAT3 shows the best performance in terms of comfort preservation, thus the improvement is primarily attributable to the dehumidifier control logic, which replaces the fixed relative humidity band with a dynamic regulation strategy.

Fig. 10 illustrates the reduction of comfort (Reduc_Comf) defined in Eq. (12) obtained for the representative methods across the three analysed climates (Italy, Spain, and Greece). This indicator quantifies the relative deviation between the representative approaches from the full summer simulation, with negative values indicating an underestimation of comfort hours. For all methods, the largest deviation occurs under the first control strategy (STRAT1), with values ranging approximately from −15% to −21%. For STRAT2, Typ demonstrates higher levels of numerical consistency, with deviations occurring mostly within a range of ±5%. However, an examination of the trends across strategies reveals that both Typ and Mac exhibit an incorrect trend, simulating fewer comfort hours for STRAT3 than for STRAT2, which contradicts the trend observed in the full summer simulation. Only Clu and Dur methods are able to reproduce this trend more accurately across the different climates, although Clu sightly fails to capture the trend in Greece.

4. Discussion

Building on the methodology previously developed for winter conditions [22], the present analysis extends the assessment of representative-day selection methods to the summer period, where cooling and dehumidification dynamics introduce additional complexity. Because latent loads represent a significant share of summer demand, a flexibility strategy is applied to modulate air relative humidity. The four representative day selection methods (Typ, Mac, Clu and Dur) are evaluated across three Mediterranean climates and multiple control strategies and their results are compared against full-summer simulations through several KPIs. The comparative analysis highlights differences in the capability of representative-day selection methods to reproduce full-summer behaviour. Overall, the results indicate that no single method systematically outperforms the others across all indicators; instead, each exhibits strengths and limitations depending on the nature of the KPI and the climatic context. This behaviour is consistent with what emerges from the literature on cooling-mode operation of heat pump systems [11], where summer dynamics are characterised by discontinuous operation, stronger dependence on solar gains, internal thermal mass. As a consequence, cooling-season duration curves tend to be more irregular and fragmented than winter ones, making summer conditions inherently more variable and harder to synthesise through a limited set of representative days. Among the different methods, Typ consistently yield the most concentrated range of daily average temperature in all cases. In contrast, Dur, reproduces the statistical distribution of the season, its construction based on duration curves compromises temporal coherence.

Dur systemically underestimates electricity consumption and, as a consequence, the associated electricity cost (Fig. 7). This behaviour is due to the selection of several days characterised by lower temperatures and reduced GHI, which artificially lowers the simulated cooling demand. As a result, Dur fails to reproduce numerical values accurately and, in some cases, does not capture the correct behavioural trends across the flexibility strategies. These limitations indicate that Dur is unsuitable for flexibility analysis.

Mac and Clu for some KPI and climates (Spain and Italy) provide the closest numerical alignment with the full-summer simulation with RMSE values below 2–3%. Nevertheless, the analysis also highlights that numerical accuracy alone does not guarantee correct behavioural representation. For instance, while Mac yields small deviations in the remaining-energy-shift KPI, it fails to preserve the correct directional trend between STRAT1 and STRAT2 in Greece and Italy. Clu, by contrast, exhibits the most stable behaviour across climates, avoiding large deviations even when it does not provide the absolute lowest RMSE.

Typ shows a good alignment in the absolute values of KPIs (Fig. 7) and proves reliable at reproducing the trend across flexibility strategies specially in Greece and Spain. In Italy, all approaches underestimate the electricity consumption, Typ slightly more than Mac and fails to capture the expected cost trend. It should be noted that electricity cost varies within a very narrow range, and flexibility strategies are ineffective as they result in negligible savings. Thus, the Italian case is less relevant than others two in determining the method that best represents the full

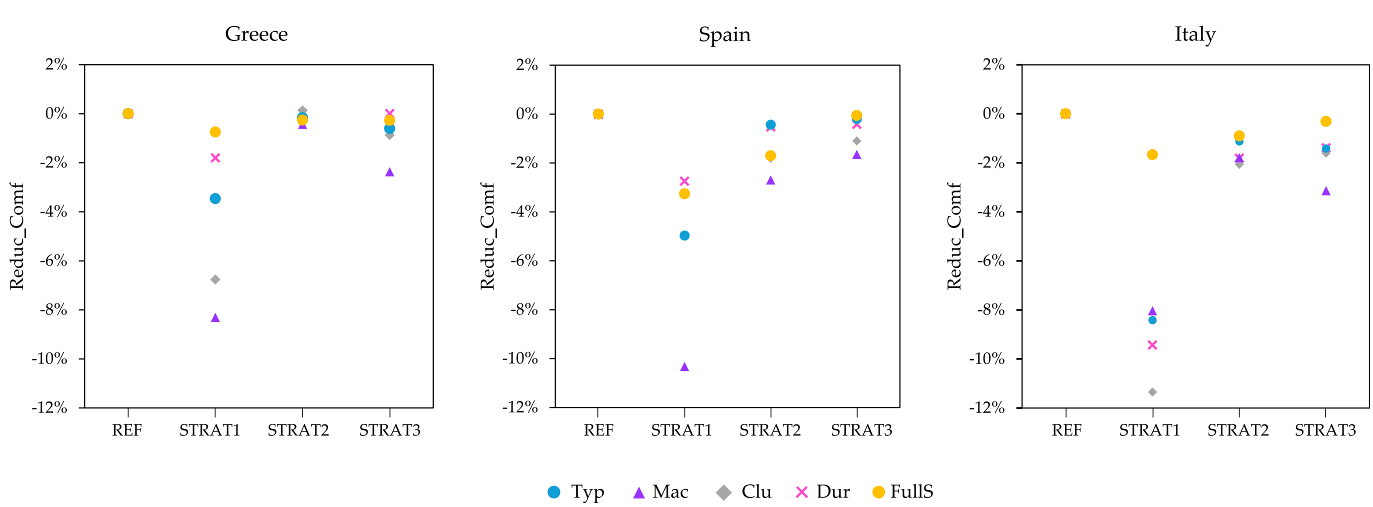

Fig. 10. Reduction of comfort among the different climates.

summer. Nevertheless, the week identified by Typ in the Italian climate gives the most regular RMSE across the different KPI (Fig. 8).

The extension of the analysis to dehumidification strategy STRAT3 shows that Typ and Mac generally maintain error values below 5–6% for the latent load distribution, confirming their suitability for seasonal-scale assessments. In contrast, Clu and Dur introduce more systematic deviations, which can be attributed to the selection of representative days with higher relative humidity. Comfort analysis demonstrates that Typ and Dur reproduce the closest values in comfort hours across climates and for different strategies.

5. Conclusion

This study evaluated the performance of four representative-day selection methods (Typ, Mac, Clu, and Dur) in reproducing full-summer building energy and flexibility behaviour across three Mediterranean climates. The analysis considered multiple flexibility strategies based on electricity prices, including a humidity control (STRAT3), and focused on key performance indicators such as energy shifting, electricity consumption and cost, latent load fraction and comfort hours.

The analysis shows that no single method consistently outperforms the others across all climates and KPIs. Dur, due to its reliance on duration curves and temporal incoherence, systematically underestimates electricity consumption and cost while overestimating demand-shifting potential, making it unsuitable for flexibility assessments that depend on peak-load dynamics. Mac achieves really good numerical accuracy but may fail to reproduce directional trends under flexibility strategies. Clu provides a robust and balanced performance, generally preserving the relative effectiveness of the strategies and maintaining moderate deviations in remaining energy shift. The Typ reliably captures the trends between the different scenarios, particularly in Greece and Spain. It tends to overestimate flexibility improvements, but it provides the most accurate absolute values for extrapolated electricity cost and energy consumption. It also performs well across indicators in the Greek case, where control strategies based on day-ahead electricity prices have the strongest impact; this makes it especially suitable for evaluating price-driven heat pump flexibility strategies.

The results from this study can be used to obtain a representative period for energy flexibility evaluations on heat pumps during the cooling season. It shows that depending on the aimed key performance indicators, a different selection procedure can be recommended, i.e. a typical week for extrapolation purposes, day clustering to allow relative comparisons between different strategies and an energy-based selection procedure for seasonal-scale assessments.

The price-driven strategies in this work adjust the heat pump operation by manipulating generally available control variables on the heat pump system without bypassing the manufacturer control. Hence, these strategies are considered to be easily applicable on heat pumps directly in the field.

Declaration of AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used DeepL and ChatGpt to support translation and writing in order to improve style and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Ana Paola Rocca Vera: Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Maarten Evens:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Paola D'Agaro:** Writing – review & editing, Writing – original draft, Validation, Supervision, Formal analysis. **Alessia Arteconi:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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.

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Data availability

Data will be made available on request.

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