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# A holistic framework for the optimal design and operation of electricity, heating, cooling and hydrogen technologies in buildings

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## HIGHLIGHTS

- Building demand, technology and energy system optimisation models are integrated.
- The framework uses open-source tools to model complex multi-energy-vector systems.
- The novel formulation is generic while capturing both short- and long-term energy storage.
- Smart integration of electrical, thermal and hydrogen systems leads to minimum cost.
- Demand patterns and resource prices greatly impact PV, heat pump and hydrogen synergies.

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## ABSTRACT

In this work, the Design and Operation of Integrated Technologies (DO-IT) framework is developed, a comprehensive tool to support short- and long-term technology investment and operation decisions for integrated energy generation, conversion and storage technologies in buildings. The novelty of this framework lies in two key aspects: firstly, it integrates essential open-source modelling tools covering energy end uses in buildings, technology performance and cost, and energy system design optimisation into a unified and easily-reproducible framework. Secondly, it introduces a novel optimisation tool with a concise and generic mathematical formulation capable of modelling multi-energy vector systems, capturing interdependencies between different energy vectors and technologies. The model formulation, which captures both short- and long-term energy storage, facilitates the identification of smart design and operation strategies with low computational cost. Different building energy demand and price scenarios are investigated and the economic and energy benefits of using a holistic multi-energy-vector approach are quantified. Technology combinations under consideration include: (i) a photovoltaic-electric heat pump-battery system, (ii) a photovoltaic-electric heat pump-battery-hot water cylinder system, (iii) a photovoltaic-electrolyser-hydrogen storage-fuel cell system, and (iv) a system with all above technology options. Using a university building as a case study, it is shown that the smart integration of electricity, heating, cooling and hydrogen generation and storage technologies results in a total system cost which is >25% lower than the scenario of only importing grid electricity and using a fuel oil boiler. The battery mitigates intra-day fluctuations in electricity demand, and the hot-water cylinder allows for efficiently managing heat demand with a small heat pump. In order to avoid PV curtailment, excess PV-generated electricity can also be stored in the form of green hydrogen, providing a long-term energy storage solution spanning days, weeks, or even seasons. Results are useful for end-users, investment decision makers and energy policy makers when selecting building-integrated low-carbon technologies and relevant policies.

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## Nomenclature

*Abbreviations*

- ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers
- ATWHP air-to-water heat pump
- CHP combined heat and power
- COP coefficient of performance
- DO-IT Design and Operation of Integrated Technologies
- EER energy efficiency ratio
- HVAC heating, ventilation, and air-conditioning
- mono-Si monocrystalline silicon
- NREL National Renewable Energy Laboratory
- PEM proton-exchange membrane
- PV photovoltaic
- RES renewable energy source

*Sets*

- $H$ hours of typical day (1…24)
- $HY$ hours of whole year (1…8760)
- $Y$ years (1…20)
- $R$ resources
- $B$ buildings
- $TD$ typical days (1…10)
- $T$ all technologies
- $CT$ energy conversion technologies
- $ST$ energy storage technologies
- $GT$ energy generation technologies

*Parameters*

- $Q_{\min}(b,t,y)$ minimum newly installed capacity if installed (kW)
- $Q_{\max}(b,t,y)$ maximum newly installed capacity if installed (kW)
- $C_{\text{inv}}(t)$ technology investment cost (EUR/kW)
- $C_{\text{inst}}(t)$ technology installation cost (EUR)
- $C_{\text{maint}}(t)$ technology maintenance cost (EUR/kW)
- $I_{\text{init}}(b,t)$ initially installed capacity at the start of the time horizon (kW)
- $L(t)$ technology lifetime (years)
- $\eta_{\text{c,v}}(ct,r,td,h)$ matrix of time-dependent efficiency conversions between energy conversion technologies and resources (−)
- $\eta_{\text{s}}(st,r)$ matrix of conversion factors between energy storage technologies and resources (–)
- $SoC_{\max}(st)$ maximum state of charge of energy storage technology (%)
- $SoC_{\min}(st)$ minimum state of charge of energy storage technology (%)
- $S_{\text{loss}}(st)$ self-discharge (time-dependent storage loss) (%/hour)
- $\tau_{\text{dur}}(st)$ minimum amount of time required to charge / discharge (hours)
- $A_{\text{s}}(gt)$ specific surface area covered by generation technology ($m^2$/kW)
- $\dot{W}_{\text{gt}}(b,gt,r,y,td,h)$ available power output from on-site generation technology (kW)
- $A_{\max}(b,gt)$ maximum available area (e.g., roof area for photovoltaic system) ($m^2$)
- $D(b,r,y,td,h)$ demand for resources (kW)
- $P_{\text{imp}}(r,y,td,h)$ price of importing resources (EUR/kWh)
- $P_{\text{exp}}(r,y,td,h)$ price of exporting resources (EUR/kWh)
- $f_C(r,y,td,h)$ carbon footprint factor of resources ($kgCO_2$/kWh)
- $a(r)$ ability to import or export resources {0,1}
- $i_{\text{r}}$ interest rate (%)
- $C_{\text{ann,inv,budget}}(y)$ annual investment budget (EUR)
- $Em_{\text{ann,CO2,budget}}(y)$ annual CO2-equivalent emissions budget (kgCO2)
- $C_{\text{tax}}(y)$ carbon tax (EUR/$kgCO_2$)
- $N(td)$ number of times a typical day appears in a year (−)
- $TDa(hy)$ typical day associated with each hour of the year (−)
- $THa(hy)$ hour of typical day associated with each hour of the year (−)

*Decision variables*

- $C_{\text{tot}}$ total system cost (EUR)
- $C_{\text{tot,inv}}(y)$ annual investment cost (EUR)
- $C_{\text{tot,op}}(y)$ annual operation cost (EUR)
- $C_{\text{tot,CO2}}(y)$ annual carbon cost (EUR)
- $C_{\text{tot,maint}}(y)$ annual maintenance cost (EUR)
- $Em_{\text{CO2}}(y)$ $CO_2$- equivalent emissions ($kgCO_2$)
- $\dot{W}_{\text{r}}(b,r,y,td,h)$ rate of production (+) or requirement (−) of resources (kW)
- $U(b,t,y)$ installation decision {0,1}
- $Q(b,t,y)$ newly installed capacity (kW)
- $I(b,t,y)$ total installed capacity (kW)
- $\dot{W}_{\text{ct}}(b,ct,y,td,h)$ power output of each energy conversion technology (kW)
- $\dot{W}_{\text{imp}}(b,r,y,td,h)$ resource imports (kW)
- $\dot{W}_{\text{exp}}(b,r,y,td,h)$ resource exports (kW)
- $\dot{W}_{\text{st}}(b,st,y,r,td,h)$ energy transferred to (+) or from (−) storage technologies (kW)
- $E_{\text{st}}(b,st,y,hy)$ energy stored (kWh)

## 1. Introduction

The simultaneous decarbonisation of electricity, heating and cooling in buildings remains a multi-faceted challenge worldwide. Advancements and cost reductions in electricity generation using photovoltaic (PV) and wind energy technologies have been remarkable in recent years [1,2]. However, heating and cooling still account for ~50% of the energy consumption in Europe, and 75% of that energy is attributed to fossil fuels [3]. In the context of buildings, reducing carbon emissions requires the development of smart technology design and operation strategies [4] for new-build developments and the subsequent deep energy renovation of existing buildings [5]. The complexity of this challenge requires advanced tools for making informed decisions regarding the optimal integration and operation of existing and emerging energy technologies [6,7].

### 1.1. Integration of photovoltaics in buildings

The integration of renewable energy sources (RES) to heating, cooling and energy storage technologies has been a field of increasing notice in academic and industrial environments. Exploiting technological solutions in a cost-effective way is essential in the global effort to accelerate the energy transition, and smart design and operation strategies of RES-integrated systems can lead to remarkable economic [8,9], environmental [10] and energy-security [11] benefits.

PV generation stands as the predominant RES in the context of building infrastructure [12]. The curtailment of PV systems, which is the process of deliberately reducing the PV electricity output below what could have been produced, is becoming a prime issue in high solar-radiation regions, as it represents wasted clean energy potential [13]. As higher penetrations of solar technologies are reached, oversupply of electricity in certain periods and subsequent curtailment can have notable economic and environmental impacts for the energy system as a whole [14] and for PV system owners themselves, who may benefit less (or not at all) from exporting electricity. Although the overbuilding of PV systems in conjunction with curtailment could also be potentially cost-effective compared to investing in expensive energy storage under certain scenarios [15], this would be associated with various risks and environmental concerns [16]. Hence, increasing the self-sufficiency of buildings, which is defined as the proportion of locally used energy that is not imported [17], is a primary objective of energy strategies set by many countries in Europe and elsewhere [18]. It is also important to note that the primary means to switch away from fossil fuels in the case of heating and cooling in buildings involves the uptake of electric vapour-compression heat pumps, the global sales of which have grown at fast speed [19], highlighting the need for the careful utilisation of PV-generated energy.

In building applications, the smart use of energy storage can reduce PV curtailment, improve the performance of heating and cooling technologies and reduce electricity imports during peak-price periods [20]. Energy storage can act as a buffer between demand and supply and is considered an imperative piece of future energy systems [21]. It is classified into short- and long-term storage. Lithium-ion batteries have high roundtrip efficiencies and are widely available, however they have relatively low lifetimes (<15 years) and are not well suited for long-duration (>10 h) applications [22]. At the same time, thermal and hydrogen energy storage systems are gaining increasing interest as they offer other benefits. Thermal energy storage is often significantly cheaper than electricity storage, while several thermo-mechanical energy storage systems could be potentially cost-effective in the future [23]. Hydrogen can offer longer storage durations, providing seasonal energy storage capabilities, while the capital cost of green hydrogen energy systems has significantly dropped in the last decade and is expected to drop further [24].

### 1.2. Critical modelling aspects in building energy systems

Efforts to identify efficient and affordable technology combinations for buildings involve comprehensive research and development, generally focusing on three critical aspects: (i) building energy modelling, to capture building electricity, heating and cooling demand requirements, (ii) technology cost and performance modelling, to analyse the characteristics of different technologies for varying design and operation conditions, and (iii) energy system modelling, to capture the interactions between energy vectors and technologies and thus identify the most cost-effective technology combinations.

The first set of useful modelling tools in the context of buildings encompasses building energy demand models, which are computer tools that assess and forecast the energy requirements and performance of buildings by considering various factors, such as geometry, construction materials, occupancy, thermal zones, and climatic conditions [25]. Several available tools are accessible, with over 200 potential options, both free and commercial, delineated in the Building Energy Software Tools Directory [26] offered by the U.S. Department of Energy. Prominent examples include EnergyPlus [27], the Quick Energy Simulation Tool (eQUEST) [28], the Transient System Simulation Tool (TRNSYS) [29], and the Integrated Environmental Solutions Virtual Environment (IESVE) [30]. These models enable the analysis of energy consumption, thermal behaviour, and overall system efficiency of a building for specific technologies and conditions. Moreover, they often extend their use to simulate various technology control strategies integrated into a building, such as thermostat control for heating, ventilation and air-conditioning (HVAC) systems or scheduling and demand-side response for lighting. Alternative approaches encompass digital twins and machine-learning methodologies, which aid in estimating or predicting renewable generation and demand [31,32]. It is important to note that each building energy model has unique characteristics, along with distinct advantages and disadvantages. Consequently, computational times and modelling results may vary, contingent upon the chosen set of inputs and objectives [33–35]. Notably, these models typically concentrate on short-to-medium term analyses and are not independently suitable for identifying optimal long-term investment decisions concerning novel technologies and systems.

The second essential set of modelling tools involves technology cost and performance models, which are necessary to capture how the characteristics of different technologies vary with size, operational strategies, and time-varying conditions. Organisations like the Danish Energy Agency [36] and National Renewable Energy Laboratory (NREL) [37] continuously compile and publish comprehensive catalogues of data for energy technologies. Additionally, several specialised tools cater to specific types of technologies, such as PV [38], battery storage [39], heating technologies [40], or hydrogen [41]. Based on such datasets, data-driven [42] or detailed techno-economic models [43] can be developed to assess the economic viability and performance characteristics of existing and novel technology options. The latter models can be used to infer values for conditions in which there is no available information (i.e., exploring how technologies could behave in uncharted scenarios), and to quantify the uncertainties related to techno-economic parameters (which could be useful in stochastic programming or deterministic simulation-based energy exercises). However, like building energy models, technology cost and performance datasets and models should be supplemented with other tools to identify optimal long-term energy technology investment and operation decisions.

The third category of useful modelling tools encompasses building energy system optimisation models. The latter are designed for performing optimal energy system design and operation. Energy system models are necessary to capture the interactions among different energy vectors, such as electricity, heat, and cold, offering insights into crucial aspects: (i) selection of technologies for installation, (ii) appropriate sizing of each installed technology, and (iii) optimal timing for technology installation [44–46]. Moreover, these models can exhibit operational optimisation capabilities, determining how existing and new technologies should interact based on predicted demand, weather conditions and prices. They also facilitate decision-making concerning resource imports and exports.

Various building-level optimisation models often focus on the design or operation of specific technologies, which can limit their ability to encompass interactions with alternative technologies and energy sources. Cedillos Alvarado et al. [47] developed a technology selection and operation model to simultaneously obtain investment and operation decisions for various combinations of combined heat and power (CHP) and organic Rankine cycle systems for buildings, but energy storage was not included in the model. Schütz et al. [48] developed a model to analyse retrofitting options for a residential building, demonstrating the benefits of simultaneously optimising the installation of PV systems and the upgrading of the building envelope. In that work, electric heat pumps were assumed to have a fixed COP during operation. Furthermore, Panagiotidou et al. [49] developed an optimisation model to examine the feasibility of cost-optimal retrofit strategies accompanied with heat pumps and solar systems in a practical setting, but the synergies among different energy vectors and the role of energy storage were not addressed. Similarly, Jennings et al. [50] proposed an optimisation approach to identify retrofit solutions. Nonetheless, their analysis did not explore the interplay between heat and other energy vectors, such as electricity and hydrogen. Additionally, Shen et al. [51] recently developed a control strategy optimisation methodology for HVAC systems in office buildings, demonstrating significant potential for carbon emission and electricity bill reductions in China, but did not consider distributed energy generation. Wang et al. [52] focused on the optimisation of the operation of dual-source heat pumps in buildings, emphasising the thermal components and neglecting investment trade-offs and impacts of energy storage. Meanwhile, Lindberg et al. [53] developed a methodology for the optimal energy system design of zero energy buildings, but only thermal energy storage was considered as a buffer between demand and supply.

In several instances, energy system optimisation models extend their use to analysing potential interconnections of buildings, such as for district heating applications [54,55]. The framework developed by Mehleri et al. [56], for example, was used to provide optimal designs of a distributed energy generation system at neighbourhood level, but energy storage was not considered, while heating and cooling profiles were assumed to be available. Wu et al. [57] developed a multi-objective optimisation model to provide retrofit options for residential communities and included thermal energy storage, while heating and electricity demands were based on typical buildings simulated with EnergyPlus. Although thermal energy storage was included, it was not compared with electrical or other forms of energy storage.

Overall, existing energy system models for buildings face two primary limitations. Firstly, they often oversimplify building energy demands and technology performance, relying on low-fidelity models that introduce uncertainties [43] and, in several cases, potentially unreliable conclusions [58]. Secondly, while some models capture detailed interactions between specific technologies, they fail to provide a holistic view of how different energy sources can synergistically combine to optimise energy utilisation.

### 1.3. Research gaps and scientific contributions

The following summary highlights the research gaps revealed in the literature review of this work:

- Existing building energy demand models and technology cost and performance models lack the capacity to independently determine optimal long-term investments for current and emerging technologies in buildings.
- Existing energy system optimisation models oversimplify the representation of building energy demand and technology characteristics, highlighting the need for more sophisticated tools capable of capturing complex interactions and trade-offs.
- There is a lack of literature on a unified framework addressing technology selection and sizing challenges in buildings, integrating open-source building energy models, technology cost-performance models, and energy system optimisation models.
- The literature does not adequately address the integration and operation of energy storage, encompassing electrical, thermal, and chemical forms, to exploit the best characteristics of each type and capture their synergies.

In this study, we contribute to the existing body of literature by introducing the Design and Operation of Integrated Technologies (DO-IT) framework, a novel tool that simultaneously optimises the selection, design, and operation of technologies within integrated electricity, heat, cold and hydrogen systems. The scientific and methodological contributions of the DO-IT framework, which constitute the novelty of this study, are outlined as follows:

- The DO-IT framework encompasses three essential modelling types required to identify optimal technologies for buildings (building energy demand, technology cost and performance, and energy system design optimisation). These are integrated within a unified framework.
- All tools utilised within the DO-IT framework are open-access and user-friendly, ensuring transparency, reproducibility, and adjustability.
- A mixed-integer linear optimisation problem is formulated with a concise and generic mathematical formulation. Using matrices of time-dependent and fixed energy conversion factors, the formulation is capable of modelling entire multi-energy vector systems and capturing interactions between energy generation, conversion and storage technologies.
- While a typical-day approach is used to reduce computational complexity, the inclusion of a two-layer formulation for seasonal energy storage retains the representation of seasonal variations in the solution space, thus enabling the identification of short- and long-term intelligent control and cross-vector flexibility strategies.
- Variables related to technology selection, sizing, and operation are optimised simultaneously, enabling the formulation of well-informed investment and operation strategies for buildings.

The DO-IT framework is used in this paper to determine the most suitable combinations of energy generation, conversion, and storage technologies under different technology availabilities, energy demands, resource prices, and technology price scenarios. Consequently, this paper presents a comprehensive analysis and discussion of synergies and trade-offs inherent in diverse design options for integrated systems encompassing electricity, heat, cold and hydrogen energy vectors.

The methods used to develop the framework are outlined in Section 2. Results are presented in Section 3, and concluding remarks are provided in Section 4.

## 2. Methods

The DO-IT optimisation framework is based on open-source tools and is easy-to-use by various stakeholders, including researchers, energy policy makers and end-users. The optimisation problem is developed and solved using the Python-based and open-source optimisation modelling language of Pyomo [59], but several other open-source and widely used programs are utilised to capture building demand, technology and resource attributes. The categories of required attributes to run the model and the outputs resulting from optimisation are summarised in Fig. 1. The modelling structure of the DO-IT framework, including the software used and the flow of data, are presented in Fig. 2. The modelling methods are discussed in detail in this section.

### 2.1. Optimisation model

The optimisation model is developed to be generic, yet comprehensive so that it can be used to capture interactions between various technologies, energy vectors, buildings and demands. The main model optimisation variables are the following:

(1) Technology selection (which technologies to install).
(2) Technology sizing (what capacity to install).
(3) Timing of investments (when to install each technology).
(4) Technology operation (when and at which level to operate each technology).
(5) Imports and exports of resources (which resources to import/export and when).

This section presents the main equations of the DO-IT optimisation model. The generic nature of the model is one of its stronger advantages, as new resources, buildings and technologies could be later added with minor or no changes in the model governing equations. The full list and definitions of all sets, parameters and decision variables are provided in the nomenclature.

The objective function to be minimised in this first version of the model is the total system cost throughout the planning horizon $C_{tot}$. This

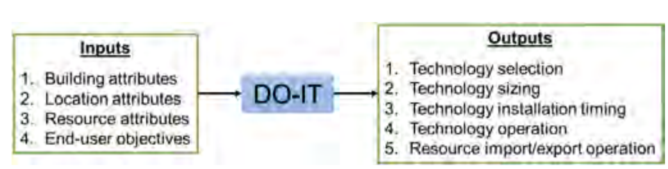


**Fig. 1.** Overview of DO-IT framework inputs and outputs.

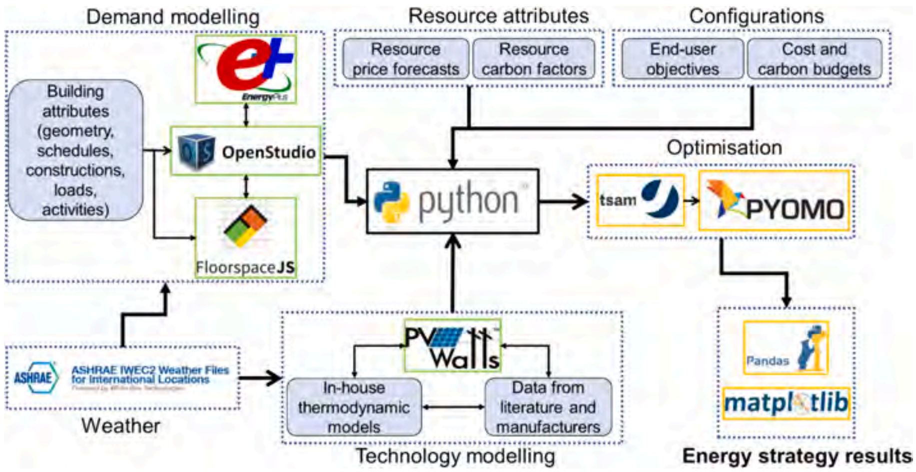


**Fig. 2.** Modelling structure of the DO-IT optimisation framework.

objective, which is widely recognised in energy system models [47], encompasses various components: the total investment cost $C_{tot,inv}$, the total operation cost $C_{tot,op}$, the total carbon cost $C_{tot,CO2}$, and the total maintenance cost $C_{tot,maint}$:

$$minC_{tot} = \sum_{y \in Y} \left( C_{tot,inv}(y) + C_{tot,op}(y) + C_{tot,CO2}(y) + C_{tot,maint}(y) \right) \bullet \frac{1}{(1+i_r)^y} \tag{1}$$

where $y$ is the year of the planning horizon and $i_r$ the inflation rate. The total investment cost in each year is obtained from:

$$C_{tot,inv}(y) = \sum_{b \in B, t \in T} \left( C_{inv}(t) \bullet Q(b,t,y) + C_{inst}(t) \bullet U(b,t,y) \right) \tag{2}$$

where $C_{inv}$ is the investment cost of each technology $t$, and $Q$ is the newly installed capacity of each technology in each building $b$. $C_{inst}$ is the installation cost of each technology and $U$ is a binary variable representing the installation decision for each technology in each building and year. An investment cost re-adjustment is made based on the technology lifetime when a technology is installed at a time at which its lifetime is longer than the time left in the time horizon.

The total operation cost is broken down to:

$$C_{tot,op}(y) = \sum_{b \in B, r \in R, td \in TD} \left( \sum_{h \in H} \dot{W}_{imp}(b,r,y,td,h) \bullet P_{imp}(r,y,td,h) - \dot{W}_{exp}(b,r,y,td,h) \bullet P_{exp}(r,y,td,h) \right) \bullet N(td) \tag{3}$$

where $\dot{W}_{imp}$ and $\dot{W}_{exp}$ are the imports and exports of each resource, respectively, at each hour $h$, typical day $td$, year $y$, resource $r$ and building $b$. $P_{imp}$ and $P_{exp}$ are the prices of importing and exporting resources, respectively, and $N$ the number of times a typical day appears every year.

The total carbon and maintenance costs are obtained as follows:

$$C_{tot,CO2}(y) = Em_{CO2}(y) \bullet C_{tax}(y) \tag{4}$$

$$C_{tot,maint}(y) = \sum_{b \in B, t \in T} C_{maint}(t) \bullet I(b,t,y) \tag{5}$$

where $Em_{CO2}$ represents the annual $CO_2$-equivalent emissions of end-users, $C_{tax}$ the carbon tax, $C_{maint}$ the maintenance cost for each technology and $I$ the total installed capacity of each technology in each building and year. The $CO_2$-equivalent emissions are based on the resource imports and time-dependent carbon footprint factors of resources:

$$Em_{CO2}(y) = \sum_{b \in B, r \in R, td \in TD} \left( \sum_{h \in H} \dot{W}_{imp}(b,r,y,td,h) \bullet f_C(r,y,td,h) \right) \bullet N(td) \tag{6}$$

where $f_C$ is the carbon footprint factor of each resource at hour, typical day and year.

The annual emissions and investment costs should be lower than the annual emission target $Em_{ann,CO2,budget}$ and annual investment budget $C_{ann,inv,budget}$, respectively, if these exist:

$$Em_{CO2}(y) \le Em_{ann,CO2,budget}(y) \tag{7}$$

$$C_{tot,inv}(y) \le C_{ann,inv,budget}(y) \tag{8}$$

New capacity installed for each technology should not be lower or higher than the minimum technology size $Q_{min}$ or maximum technology size $Q_{max}$ available on the market at that price:

$$Q(b,t,y) \le Q_{max}(b,t,y) \bullet U(b,t,y) \tag{9}$$

$$Q(b,t,y) \ge Q_{min}(b,t,y) \bullet U(b,t,y) \tag{10}$$

The installed capacity at each year is the sum of the capacity of the previous year and newly installed capacity, minus any capacity that reached the end of its lifetime:

$$I(b,t,y) = I(b,t,y-1) + Q(b,t,y) - Q(b,t,y-L(t)) \tag{11}$$

where $L$ is the lifetime of each technology. The above equation is slightly different for the first year of the time horizon (i.e., when $y = 1$), where $I(b,t,1) = I_{init}(b,t) + Q(b,t,1)$, instead. It is also different in early years in the time horizon (i.e., before the technology end of life is reached), for which the last part ($Q(b,t,y-L(t))$) of the equation is omitted.

The rate of production of resources $\dot{W}_r$ at each timestep depends on the output of all energy conversion technologies $\dot{W}_{ct}$, their time-dependent efficiencies $\eta_{c,v}$ and the output of all on-site generation technologies $\dot{W}_{gt}$. Negative values correspond to resources being required instead of produced:

$$\dot{W}_r(b,r,y,td,h) = \sum_{ct \in CT} \dot{W}_{ct}(b,ct,y,td,h) \bullet \eta_{c,v}(ct,r,td,h) + \sum_{gt \in GT} \dot{W}_{gt}(b,gt,r,y,td,h) \tag{12}$$

The output of energy conversion technologies should always be less than their installed capacity:

$$\dot{W}_{ct}(b,ct,y,td,h) \le I(b,ct,y) \tag{13}$$

The maximum capacity of energy generation technologies depends on the maximum available area $A_{\max}$ that is made available for them at each building:

$$I(b,gt,y) \bullet A_s(gt) \leq A_{\max}(bgt) \tag{14}$$

where $A_s$ is specific surface area covered by the generation technology.

The law of conservation of energy states that the demand $D$ for each resource in each building and time is always equal to the sum of resources produced, resources exchanged with the grid (for resources for which this option is available) and resources exchanged with energy storage technologies $\dot{W}_{st}$:

$$D(b,r,y,td,h) = \dot{W}_r(b,r,y,td,h) + \left(\dot{W}_{imp}(b,r,y,td,h) - \dot{W}_{exp}(b,r,y,td,h)\right) \bullet a(r) - \sum_{st \in ST} \dot{W}_{st}(b,st,r,y,td,h) \tag{15}$$

where $a$ is the ability to import or export any given resource.

The challenge of aggregating hourly demand and supply profiles for typical days arises from the independent modelling of these days, which means that no energy can be exchanged between them. For this purpose, an approach similar to that found in the work of Kotzur et al. [60] is used. This method enables the model to incorporate seasonal storage dynamics. The amount of energy exchanged with energy storage at each hour is not indexed by typical day and hour, but it is instead indexed by the typical day $TDa$ and the hour $THa$ of the typical day that are associated with each hour of the whole year $hy$. Each storage technology can be used to store a certain set of resources and has a given storage efficiency $\eta_s$ [60]:

$$E_{st}(b,st,y,hy) = E_{st}(b,st,y,hy-1) \bullet (1 - S_{loss}(st)) + \sum_{r \in R} \dot{W}_{st}(b,st,r,y,TDa(hy), THa(hy)) \bullet \eta_s(str) \tag{16}$$

where $E_{st}$ is the amount of energy stored at each hour of the year and $S_{loss}$ the time-dependent storage loss of each technology.

The above equation is slightly different for the first hour of the year (i.e., when $hy = 1$), so that the energy stored at the beginning of the horizon is equal to the amount of energy stored at the end of it. If $\eta_s(st,r) = 0$, then $\dot{W}_{st}(b,st,r,y,td,h) = 0$, otherwise

$$-\frac{I(b,st,y)}{\tau_{dur}(st)} \leq \dot{W}_{st}(b,st,r,y,td,h) \leq \frac{I(b,st,y)}{\tau_{dur}(st)} \tag{17}$$

where $\tau_{dur}$ is the minimum amount of time required to charge or discharge a given energy storage technology. The amount of energy stored in each storage technology is limited by the minimum state of charge $SoC_{\min}$ and maximum state of charge $SoC_{\max}$ and its maximum installed capacity:

$$SoC_{\min}(st) \bullet I(b,st,y) \leq E_{st}(b,st,y,hy) \leq SoC_{\max}(st) \bullet I(b,st,y) \tag{18}$$

The results are analysed using the open-source data analysis Python-based tool of Pandas [61]. Visualisations are created using the open-source Python-based library of Matplotlib [62].

### 2.2. Demand modelling and weather data

The building energy consumption model of the DO-IT framework involves the use of NREL's EnergyPlus [27] simulation software. EnergyPlus, which is being continuously updated by NREL, is an open-source energy simulation engine serving as the core building design tool for the U.S. Department of Energy and one of the most extensively used building energy simulation programs worldwide [63]. Based on the available information related to the building or set of buildings under consideration, annual hourly profiles of electricity, space cooling, space heating and hot-water demand are obtained. EnergyPlus employs advanced building physics algorithms to simulate heat transfer (through conduction, convection and radiation), while it includes modelling of the air and moisture movement, light distribution and water flows.

To access EnergyPlus, the open-source application programming interface of OpenStudio [64] is used. The OpenStudio Application, which is maintained by the OpenStudio Coalition [65], allows users to input several building attributes to inform the model and acquire reliable energy consumption profiles: (i) schedules, which refer to time-dependent data sets that define how occupancy, lighting power, thermostat temperatures and other factors change with time, (ii) constructions, that define the materials of walls, floors, ceilings, doors and windows, (iii) loads, that define the consumption of people and equipment, (iv) space types and thermal zones, which define different characteristics for different rooms, (v) building geometry, which defines the heat transfer characteristics, and (vi) heating, ventilation, air-conditioning and water systems. Furthermore, EnergyPlus provides a set of resources to automate the development of prototype typical building models. Although EnergyPlus allows for the simulation of various types of HVACs, this option is not considered here; the program is only used to obtain hourly energy consumption profiles for a typical year and then use them to identify technology choice and operation strategies with the DO-IT optimisation model.

Weather data are necessary for both demand and technology modelling. The ambient air and ground temperature, humidity, wind speed, and solar irradiation affect the energy consumption of buildings (e.g., heating and cooling demand) [27]. Similarly, they affect the performance of various energy generation and conversion technologies (e.g., PV systems, heat pumps). In the DO-IT framework, weather data are processed in EnergyPlus weather format, so that they are used within the EnergyPlus program to obtain energy consumption profiles. Weather files in this format are already available for >3000 locations worldwide [27] and these can be later altered to also model the weather characteristics of additional locations.

### 2.3. Technology modelling

In the DO-IT framework, the cost and performance of technologies are estimated using detailed techno-economic models arising either from comprehensive thermodynamic and component-costing approaches or from data collected from manufacturers. In the effort to capture interactions between fossil fuels, electricity, heat, cold and hydrogen for buildings, the technologies that are considered in this first version of the model are: a fuel oil boiler, a monocrystalline silicon (mono-Si) PV system, a lithium-ion battery, an air-conditioning unit, an electric air-to-water heat pump, a hot-water cylinder, a proton-exchange membrane (PEM) electrolyser, a PEM fuel cell CHP system and a pressurised-hydrogen storage system.

The way technologies and energy vectors interact in the DO-IT framework is presented in Fig. 3. Electricity can either be produced from an on-site PV system or imported from the main grid. It can then be used to: (i) satisfy the electricity demand, (ii) drive air-conditioning units to provide cooling, (iii) drive an air-to-water heat pump to generate heat, or (iv) if excess electricity is available, drive an electrolyser to generate hydrogen. Fuel oil (or natural gas) can be imported to drive a boiler for heat provision. Electricity, heat and hydrogen can be at any time stored in appropriate electricity, heat and hydrogen storage systems. Hydrogen can be at any time converted back to electricity, while the fuel cell exhaust heat can be recovered through a heat exchanger to heat water.

Space heating and hot water are supplied through either the fuel oil boiler, the electric air-to-water heat pump (ATWHP), or the fuel cell CHP system. For space heating, the heat is presumed to be conveyed to the indoor environment using radiators. The temperature of the hot water consumed in buildings is set to 55 °C. This is assumed to match the temperature required for the water flowing through radiators, which is reasonable for modern radiators [8]. This temperature can be achieved

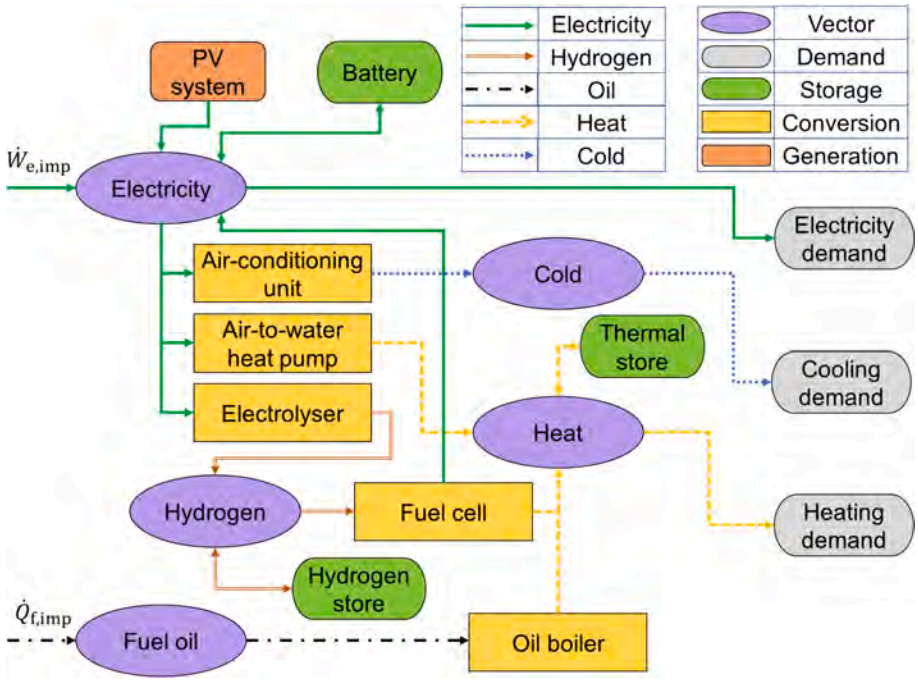


**Fig. 3.** Interactions of technologies and energy vectors in the DO-IT framework.

by all the considered heating technologies (boiler, heat pump, and fuel cell CHP). Space cooling is facilitated by conventional electric air-conditioning units, which are essentially air-to-air heat pumps. The electric ATWHP is assumed not to be able to provide space cooling, as this would require additional equipment such as ducts and condensation avoidance measures, which is not cost-effective in small-building applications.

Cost and performance attributes for the considered technologies in the DO-IT framework are presented in Table 1 and Table 2. In this paper, the specific price is defined as the total commercial technology price over the rated technology energy output, whether that is in electrical, thermal or hydrogen form. For energy storage systems, roundtrip efficiency is defined as the ratio of the energy output during discharging to the energy input during charging. For batteries, this corresponds to the electricity output over electricity input. Similarly, for thermal storage systems, it corresponds to thermal output over thermal input, while for hydrogen storage systems, it corresponds to the hydrogen output over the hydrogen input. The roundtrip efficiency definition does not include self-discharge, which is the phenomenon that causes some of the stored energy to be consumed with the passage of time due to losses, even when a storage system is not in use.

**Table 1**
Main cost and performance characteristics of energy generation and conversion technologies in the DO-IT framework. The efficiency and cost of the electrolyser include losses and costs due to hydrogen compression. The temperature $T_{amb}$ represents the outside air temperature. Specific prices of technologies correspond to energy generation and conversion power capacities lower than 20 kW. In instances where the optimisation process leads to the selection of higher installed capacities, it is assumed that multiple units of the same technologies are installed in parallel.

| Technology | Efficiency | Specific price | Lifetime |
|---|---|---|---|
| Mono-Si PV system | 19% | 950 EUR/kW$_e$ | 20 years |
| Fuel oil boiler | 80% | 80 EUR/kW$_{th}$ | 15 years |
| Air-conditioning system | $EER = 11.0e^{-0.029T_{amb}}$ | 300 EUR/kW$_{th}$ | 20 years |
| Air-to-water heat pump | $COP = 2.92e^{0.028T_{amb}}$ | 500 EUR/kW$_{th}$ | 20 years |
| PEM electrolyser | 75% | 4300 EUR/kW$_{H2}$ | 5 years |
| PEM fuel cell CHP system | 40% electrical and 40% thermal | 2600 EUR/kW$_e$ | 5 years |

**Table 2**
Main cost and performance characteristics of energy storage systems in the DO-IT framework. Specific prices of technologies correspond to energy storage capacities lower than 20 kWh. In instances where the optimisation process leads to the selection of higher installed capacities, it is assumed that multiple units of the same technologies are installed in parallel.

| Technology | Roundtrip efficiency | Specific price | Self-discharge | Lifetime |
|---|---|---|---|---|
| Lithium-ion battery | 88% | 500 EUR/kWh$_e$ | 0.040%/hour | 10 years |
| Hot-water cylinder | 98% | 80 EUR/kWh$_{th}$ | 0.649%/hour | 20 years |
| Pressurised-hydrogen tank | 100% | 10 EUR/kWh$_{H2}$ | ~ 0 | 20 years |

The case study presented in this paper focuses on a small-office application. Based on this, technology price estimates are selected to align with the average specific prices derived from a variety of manufacturers and literature sources for energy generation and conversion systems with power capacities below 20 kW, and energy storage systems with energy capacities below 20 kWh. In instances where the optimisation process leads to the selection of higher installed capacities, it is assumed that multiple units of identical technologies are installed in parallel. The incorporation of economies of scale for systems with higher capacities will be addressed in subsequent model versions.

The PV system is modelled using the open-source PVWatts Calculator [66], which, for the provided location and weather data, is used to estimate the hourly electricity generation for a whole typical year. The PV system is assumed to be made of mono-Si modules with an efficiency of 19%, anti-reflective coatings (corresponding to a temperature coefficient of −0.35%/°C), a fixed roof mount, an inverter efficiency of 96%, a tilt angle of 30°, an azimuth angle of 180°, system losses of 14% (attributed to soiling, shading, mismatch, wiring and connections) and a lifetime of 20 years. These are based on NREL's assumptions for the physical characteristics of typical high-performance PV systems [67]. The specific price is assumed to be 950 EUR/kW$_e$, which corresponds to the average price of 27 different PV panels from 6 manufacturers based on the library of Olympios et al. [40].

The fuel oil boiler efficiency and specific price are set to 80% and 80 EUR/$kW_{th}$, respectively [40]. The performance characteristics of the air-conditioning system and the electric ATWHP vary significantly with weather. The most common measures to represent their efficiency are the energy efficiency ratio (EER) and the coefficient of performance (COP), which correspond to the ratio between cooling output and electricity input (air-conditioning system), and ratio between heating output and electricity input (heat pump), respectively. The specific price and the relationship between efficiency and air temperature, which are based on hundreds of commercially available units [40], are shown in Table 1. For the calculation of these efficiencies, the hot-water delivery temperature is assumed to be equal to 55 °C, and the indoor environment target air temperature is equal to 21 °C [8,19].

The efficiencies of the PEM electrolyser and fuel cell CHP system, unlike heat-pumping technologies, do not experience noticeable changes for different ambient temperatures. Assuming stacks are operated at full load, their efficiencies can be considered relatively constant [24]. For the electrolyser, electricity-to-hydrogen efficiency at full load is here assumed to reach 80% based on the higher heating value (HHV), but this is reduced by ~5% due the hydrogen compression at the exit of the electrolyser (in order for the hydrogen to be stored in the pressurised-hydrogen storage system at ~60 bar) [24]. The hydrogen-to-electricity and hydrogen-to-heat efficiencies of the fuel cell CHP system are both assumed to be equal to 40% (HHV) [24,68]. The specific prices of the electrolyser (including compression) and fuel cell are set to 4,300 EUR/$kW_{H2}$ and 2,600 EUR/$kW_e$, respectively, and their lifetime is set to 5 years [24]. Electrolyser and fuel cell assumptions are based on detailed thermodynamic and component-costing models from Arsalis et al. [24]. It is important to mention, however, that electrolysers and fuel cells are emerging technologies with significant cost uncertainties which will be captured in later model versions.

The lithium-ion battery is assumed to have a roundtrip efficiency of 88%, a charge and discharge duration of 4 h, a self-discharge 0.040%/day, a lifetime of 10 years, a minimum state of charge of 30% and a specific price of 500 EUR/$kWh_e$, in line with NREL's System Advisor Model [69]. The hot-water cylinder has a significantly lower cost (80 EUR/$kWh_{th}$), a longer lifetime (20 years) and it can be fully discharged, but it also has higher time-dependent storage losses (0.649%/day) [8]. Lastly, the pressurised hydrogen storage system can be fully charged/discharged, has negligible losses with time [70] and costs 10 EUR/$kWh_{H2}$ [71]. Installation costs (labour, metering, piping, etc.) are assumed to be fixed at 1,500 EUR for the fuel oil boiler [72] and air-conditioning systems, 3,000 EUR for the PV system [72], 2,200 EUR for the heat pump [8], and 1,500 EUR for the storage systems. Electrolyser and fuel cell installation costs are assumed to be 3,000 EUR and maintenance costs are assumed to be equal to 1% of the capital cost for all technologies.

### 2.4. Time-series aggregation

Modelling complicated energy systems with high-fluctuation energy demand and supply is computationally demanding. For this reason, time-series aggregation is used to reduce the computational effort of optimisation models [73]. In this work, the Python package of "Tsam" [74] is used to aggregate all weather and demand data in typical days, so that the complexity is substantially reduced. A k-means clustering method is used to group the data and the model is configured to include extreme typical days of the year (days with maximum heating and cooling energy demand) in the clustering set. Including these extreme days is necessary to ensure that the selected design and operation strategies are such that the demand for electricity, heating and cooling can always be met.

### 2.5. Case study: Building construction, weather, resource prices and carbon factors

In this paper, the Living Lab of the FOSS Research Centre for Sustainable Energy at the University of Cyprus, which is located in Nicosia, Cyprus, is used as a case study. The lab has been modelled using the FloorspaceJS web-based geometry editor of OpenStudio. Building attributes are based on work schedules, construction, lightning systems and usage of equipment in the lab by researchers, staff and students. Materials are based on standards for climate zone "2A", which is the zone corresponding to Nicosia in Cyprus according to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [75]. Weather data are obtained in EnergyPlus format for Nicosia from the database of "Climate.OneBuilding" [76]. The demand model was validated against electricity demand data collected for the lab in 2022. Weather data are obtained in EnergyPlus format for Cyprus using the International Weather for Energy Calculation database of ASHRAE [77]. The annual weather characteristics represent a typical year in the considered location. It is noted that the lab is generally closed at nights and every weekend, a characteristic that is captured by the demand profiles.

The price of importing electricity is based on the commercial and industrial use tariffs published by the Electricity Authority of Cyprus in 2022 [78]. The monthly seasonal two-rate tariff is used and fuel price re-adjustment is applied based on current fuel prices. Based on this, the electricity price is set equal to 0.42 EUR/$kWh_e$ between 16:00–22:00 in the summer, while it varies between 0.23 and 0.27 EUR/$kWh_e$ for the rest of the time depending on the season and period of the day. In an effort to maximise self-sufficiency, it is assumed that electricity cannot be exported, and that PV curtailment is avoided. The price of fuel oil in Cyprus is assumed to be equal to 1.06 EUR/l (i.e., 0.09 EUR/$kWh_{oil}$) [79]. The carbon footprint of electricity in Cyprus is currently at 0.60 $kgCO_2/kWh_e$ [79], while the carbon footprint of fuel oil in residential applications is at 0.22 $kgCO_2/kWh_{oil}$ [80]. The carbon footprint of electricity is assumed to be reduced by ~2%/year, and a carbon tax (tax per unit of end-user emissions) of 0.10 EUR/$kgCO_2$ is applied throughout the time horizon in line with the Cyprus' Integrated National Energy and Climate Plan scenarios [81]. A discount rate of 3% is assumed for all technologies. The time horizon for the optimisation exercise is set to 20 years.

In the DO-IT optimisation model, we assume that in the baseline case the electricity demand is met through grid imports, and air-conditioning systems and a fuel oil boiler are already in place to cover all space cooling and heating demand, respectively. The air-conditioning systems and oil boiler are assumed to have 10 and 5 years of life left, respectively. Although a 40-$kW_e$ PV system and a 60-$kWh_e$ battery system were installed in the lab in 2023, these are not included in the initial conditions to allow the DO-IT framework to identify the optimal technology combinations through optimisation. For space heating, the heat is assumed to be transferred to the indoor environment using radiators.

The optimisation exercise determines the optimal selection of technologies, but also the optimal timing at which electricity, heat and hydrogen are produced, stored and used. The objective is to identify the best possible future technology portfolio while minimising the total system cost for the considered planning horizon.

## 3. Results

In this section, the results of the case study are presented. In Section 3.1, the hourly electricity, hot-water, space heating and space cooling requirements are determined, organising all data into typical days. In Section 3.2, optimisation results are obtained for the selection and sizing of multi-energy vector technologies across technology availability scenarios. To demonstrate how the model performs in terms of operational optimisation, Section 3.3 provides examples of time-resolved results. Section 3.4 investigates the impact of different demand and price considerations on technology selection and sizing and Section 3.5 provides further discussion, limitations, and future work opportunities.

### 3.1. Living lab demand and typical day profiles

An overview of the geometry of the FOSS Living Lab office spaces as modelled in FloorspaceJS of OpenStudio is shown in Fig. 4. The total lab area is 380 $m^2$. EnergyPlus is used to simulate the hourly energy consumption profiles for a typical year based on the provided construction sets, thermal zones, schedules and patterns. The k-means clustering approach is then used to group the weather, resource and demand data into hourly profiles for 10 typical days to represent each year.

The clustered data and the full-year demand profiles for the electricity, heating and cooling demand are shown in Fig. 5 and in Fig. 6, respectively. The simulations highlight a pronounced need for cooling, owing to Nicosia's intense summer heat. Additionally, notable energy requirements for heating in the winter are evident. It is important to state that the FOSS Living Lab is only used as a case study, but modelling techniques can be used to model the demand of various other buildings.

### 3.2. Optimal technology mix and system cost for different technology availability scenarios

The DO-IT optimisation framework can be used to devise comprehensive and multi-energy-vector solutions for building decarbonisation problems. This is here demonstrated by solving the optimisation problem for the FOSS Living Lab (i.e., using the demand profiles obtained in Section 3.1) for different combinations of technologies being assumed to be available for installation and operation. The investigated combinations of available technologies are shown in Table 3. It is important to note that the availability of a technology for installation does not guarantee its selection. Rather, it signifies inclusion as one of the viable options within the optimisation problem.

In Figs. 7–10, the optimal investment plan and mix of installed technologies in the 20-year horizon for the four optimised cases is provided with 5-year intervals. The results for the total system cost, investment and installation cost, operation and carbon cost are summarised for all cases in Fig. 11. The aggregated annual energy generation, imports and self-sufficiency at the end of the planning horizon are also provided for all cases in Table 4 and Table 5. The computational time required for these simulations consistently fell within the range of 0.2 to 2 min, depending on the number of technologies under consideration.

In the baseline case, it is assumed that electricity and cooling demand are always met by importing electricity from the grid, while the heating demand is met solely by a fuel oil boiler for the whole planning horizon. The operation and carbon costs are in all cases based on the use of fuel oil and grid-imported electricity. Year 0 in Figs. 7–10 shows the initial technologies in place before any optimisation. The air-conditioning systems are always replaced at the end of their lifetime with identical units (as no other cooling generation or storage technologies are considered). In all optimised scenarios, it is shown that fuel oil boilers are phased out once they reach the end of their lifetime.

In Optimised Case 1, a small heat pump capacity is initially installed (4 $kW_{th}$), and a further heat pump capacity is installed (15 $kW_{th}$) after the end of lifetime of the boiler, as shown in Fig. 7(a). The optimisation result shows that it is worth investing in a small lithium-ion battery (6 $kWh_e$) accompanied by an investment in a small PV system (4 $kW_e$). The battery is replaced as soon as its lifetime is over (Fig. 7(b)). The total system cost in Optimised Case 1 is 115,000 EUR (Fig. 11), which is 16% lower than the total system cost associated with the Baseline Case (136,000 EUR).

In Optimised Case 2, when a hot-water cylinder is also considered available (Fig. 8), the investment strategy and technology mix change only slightly when compared to Optimised Case 1. Instead of installing an additional heat pump capacity once the oil boiler is out of operation, the optimisation result shows that, it is wiser to install a 12 $kW_{th}$ hot-water cylinder. One of the main benefits of thermal energy storage when compared to electrical storage is that it is significantly cheaper, so the optimisation result tends towards thermal rather than electrical energy storage, whenever this is possible (i.e., for addressing the fluctuating heating demand). The total system cost in this case is 110,000 EUR (Fig. 11), which is 4% lower than that of Optimised Case 1 and 20% lower than the Baseline Case.

In both Optimised Cases 1 and 2, the optimised operation of the battery and hot-water cylinder involves using them to only store energy for a few hours; despite the ability of the model to capture seasonal energy storage, this option is not chosen in these cases. The main reason for this is the inability of these technology options to store energy for more than a few hours without significant losses (i.e., due to self-discharge). However, results differ significantly in Optimised Case 3, where no battery or hot-water cylinder are considered available. Instead, the only available storage medium in this case is compressed hydrogen, while the only available heat provision option is the fuel cell CHP system. Due to this reason, a significant amount of PV capacity (26 $kW_e$) is installed once the boiler lifetime is over, in conjunction with a 13 $kW_{H2}$ electrolyser, a 15 $kW_e$ / 15 $kW_{th}$ fuel cell CHP system and a pressurised tank of notable hydrogen capacity (200 $kWh_{H2}$), as shown in Fig. 9. The large initial investments in Optimised Case 3 are attributed to the use of the considered technologies to perform weekly and seasonal energy storage. Some amounts of hydrogen can be produced in weekends or in high-solar-radiation weekdays in summer, and the fuel cell CHP system is used to cover the whole heat demand in conjunction with a significant amount of the electricity demand in the winter. It is clear from Fig. 11 that, in this case, the total operation cost is much lower than the other cases. However, the large up-front costs and the relatively low total system electrical and thermal efficiency of the electrolyser-hydrogen-fuel cell system (~ 60%) result in a higher total system cost in Case 3 (256,000 EUR). It should be mentioned, though, that this case is also characterised by a much higher building self-sufficiency at the end of the time horizon (95% compared to 25% in the previous cases).

Lastly, in Optimised Case 4, when all technologies are considered available, it is interesting to observe that the optimisation solution includes a combination of all of them. The most interesting result is the simultaneous installation and smart use of all types of energy storage: electrical, thermal and hydrogen. In detail, by the end of the time horizon, the capacities of battery, hot-water cylinder and hydrogen storage are equal to 22 $kWh_e$, 12 $kWh_{th}$ and 177 $kWh_{H2}$, respectively (Fig. 10). It is useful to note that hydrogen generation and utilisation technologies are much smaller in Optimised Case 4 than in Optimised Case 3, resulting in lower amounts of electricity and hydrogen generation (Table 4). The fact that hydrogen is interacting with various forms of energy storage enables the installation of a small-scale electrolyser generating hydrogen using electrical energy from a battery at a consistently low capacity. Simultaneously, a fuel cell can efficiently generate heat at a steady low capacity, which can be stored in a hot-water cylinder to be used when required. Thus, the simultaneous operational optimisation of all energy vectors facilitates the intelligent utilisation of hydrogen without the requirement for large, costly electrolysers and fuel cells. In Optimised Case 4, the battery is used to balance most of the fluctuations during a day, while hydrogen storage is mainly used to store energy in periods of high PV generation for a few days, weeks or even seasons (e.g., low-demand weekends are used for hydrogen generation). The use of thermal energy storage means that peak-heating-demand periods can be handled well with a small heat pump unit. The total system cost in Optimised Case 4, which involves using synergies between all energy vectors, is equal to 101,000 EUR (Fig. 11), which is 26% lower than the Baseline Case, thus demonstrating the significance of thinking holistically when designing multi-energy-vector systems. The self-sufficiency at the end of the time horizon is equal to 91% (Table 5).


**Fig. 4.** Geometry of the Living Lab of the FOSS Research Centre for Sustainable Energy, University of Cyprus, as designed using the FloorspaceJS web-based geometry editor of OpenStudio: (a) 3D view and (b) floorplan.

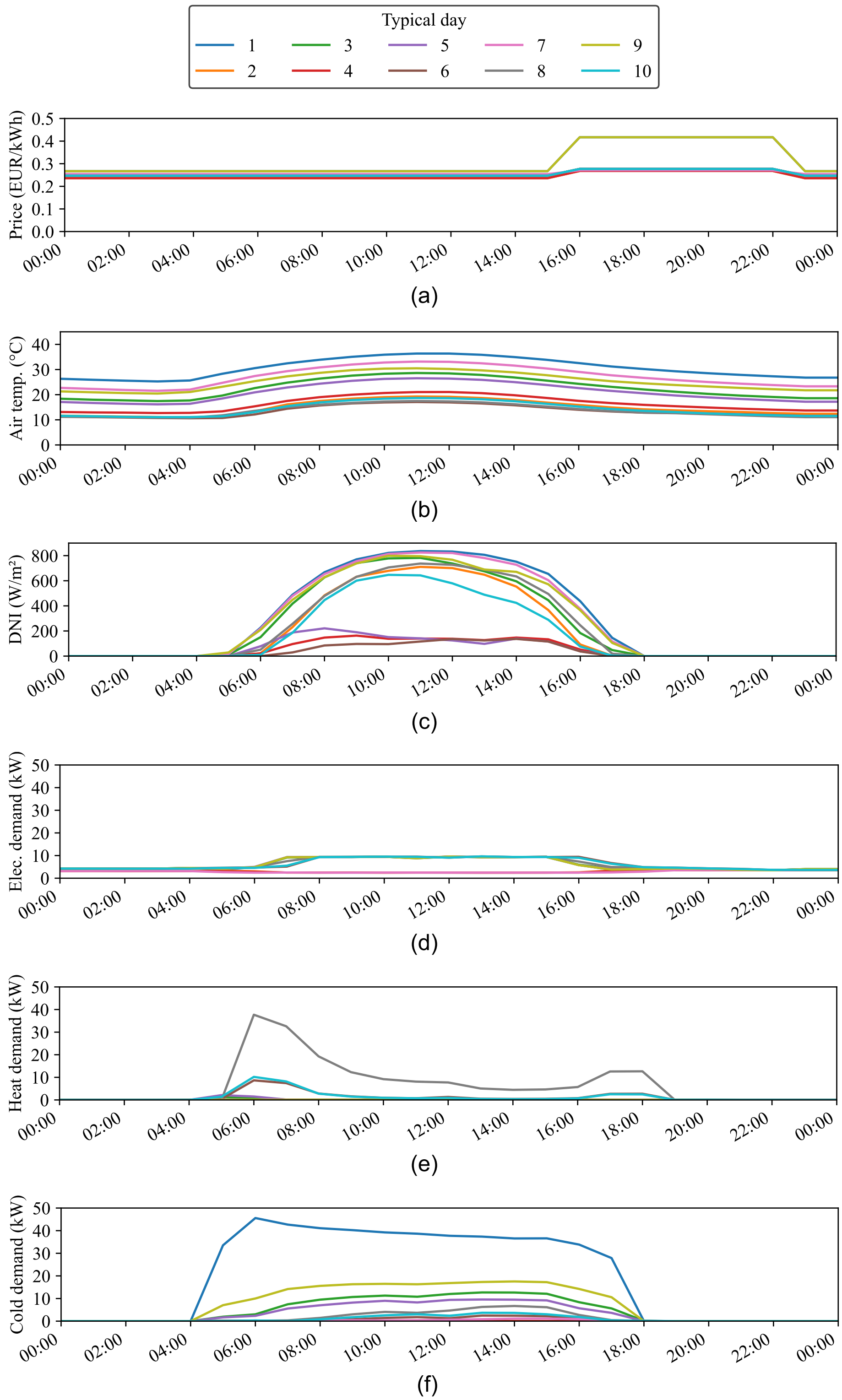


**Fig. 5.** Typical day clustering for a full year: (a) importing electricity price; (b) air temperature; (c) direct normal irradiance; (d) electricity demand; (e) heating demand; and (f) cooling demand.

### *3.3. Optimal operation examples through time-resolved analysis*

The DO-IT optimisation framework is able to provide optimal operation strategies based on time-of-use electricity price tariffs and weather conditions. To demonstrate these, three examples are shown here in Fig. 12 and Fig. 13, corresponding to three different typical days for Optimised Case 4 (which involves all available technologies) for (a) a typical working day with a small amount of heating demand and high electricity prices in the afternoon, (b) a typical working day with high cooling demand and high electricity prices in the afternoon, and (c) a typical cold weekend day with negligible demand.

In the typical working day of Fig. 12(a) and Fig. 13(a), characterised by a substantial demand for electricity demand and a minor heat demand, electricity is generated from the on-site PV system between

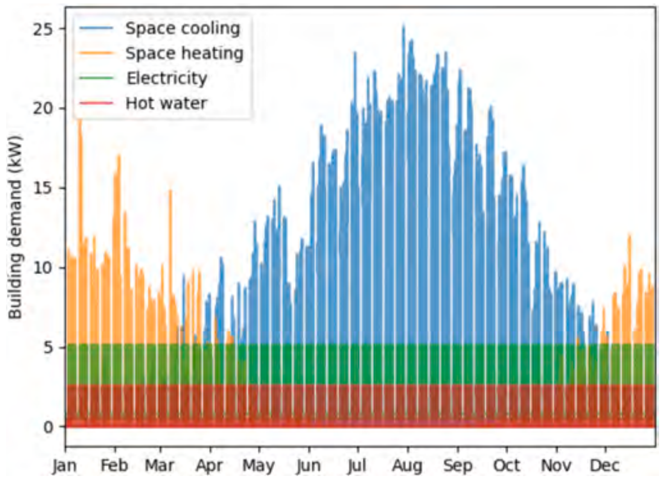


**Fig. 6.** Electricity, space heating, space cooling and hot-water annual hourly demand profiles for the FOSS Living Lab as simulated using the EnergyPlus software.

**Table 3**
Combinations of technologies that are assumed to be available to be installed.

| Case | Combination of technologies |
|---|---|
| Baseline Case | Fuel oil boiler + Air-conditioning unit |
| Optimised Case 1 | Fuel oil boiler + Air-conditioning unit + Mono-Si PV system + ATWHP + lithium-ion battery |
| Optimised Case 2 | Fuel oil boiler + Air-conditioning unit + Mono-Si PV system + ATWHP + lithium-ion battery + hot water cylinder |
| Optimised Case 3 | Fuel oil boiler + Air-conditioning unit + Mono-Si PV system + PEM electrolyser + compressed $H_2$ storage + PEM fuel cell CHP system |
| Optimised Case 4 | Fuel oil boiler + Air-conditioning unit + Mono-Si PV system + ATWHP + lithium-ion battery + hot water cylinder + PEM electrolyser + compressed $H_2$ storage + PEM fuel cell CHP system |

around 06:00–18:00. As shown in the negative segment of Fig. 12(a), the generated electricity serves multiple purposes: (i) fulfilling the electricity demand in this time period, (ii) driving an air-source heat pump to produce heat, and (iii) storing some electrical energy in the battery. During the afternoon (16:00–20:00), when there is still some electricity demand and the electricity prices are high, no electricity is imported. Instead, the stored electricity from the battery is utilised to meet the demand. Additionally, noteworthy is the observation of the energy conversion to heat with the heat pump. As shown in Fig. 13(a), the heat pump operation does not exactly follow the heat demand. Instead, the heat pump optimally leverages heat released from the hot-water cylinder in the early hours (00:00–12:00) and subsequently replenishes this heat during the lower-demand afternoon period (12:00–20:00). The use of thermal energy storage enables the air-source heat pump to be sized to be smaller than what would be required if it were mandated to directly meet the whole heat demand. It also allows the use of the heat pump during high-temperature periods, when its COP is high.

Another similar example is shown in Fig. 12(b) and Fig. 13(b), which involve a typical working day with high cooling demand and high electricity prices in the afternoon. The electricity generated from the on-site PVs is again used to fulfil the electricity demand between around 06:00–18:00, but this time some part of it is also used to drive the air-conditioning systems to provide cooling. Since no cold storage technology is considered, the air-conditioning system operation follows the cooling demand (Fig. 13(b)). Again, during high-price afternoon periods, there is no reliance on imported electricity, as a certain amount of electrical energy is stored in the battery during the morning to anticipate and fulfil the demand later in the day. It is also interesting to observe that a small amount of electricity is imported around midday, when prices are lower, in order to ensure that the battery has sufficient energy to meet the electricity demand during the high-price afternoon hours.

Lastly, a typical cold weekend day with negligible demand is presented in Fig. 12(c) and Fig. 13(c). On weekends, since the demand for electricity, heating and cooling are limited, on-site PV generation is used in two main ways: (i) storing electricity in a battery for later use, and (ii) producing green hydrogen. Although the conversion of electricity to green hydrogen is costly and involves significant energy losses, the model opts for this storage method due to its ability for prolonged storage and future use during high-demand days. As shown in Fig. 13(c), all generated hydrogen over the weekend is stored for later deployment.

By benefiting from the advantages of all considered technologies, on-site PV generation is achieved without any curtailment and with high self-sufficiency, minimising operational costs.

### *3.4. Optimal technology sizing for different technology prices, building demands and electricity prices*

The DO-IT framework has been intentionally designed for broad applicability and ease of adaptation across different technology assumptions and building contexts. Although focus in this study was placed on specific technology prices, resource prices and an office construction in Cyprus, it is crucial to note the versality of the framework for extending energy strategy recommendations to different cost assumptions and buildings with varying energy demands. In this section, we provide a comprehensive analysis of how technology sizing is impacted by different technology cost assumptions and building energy demands.

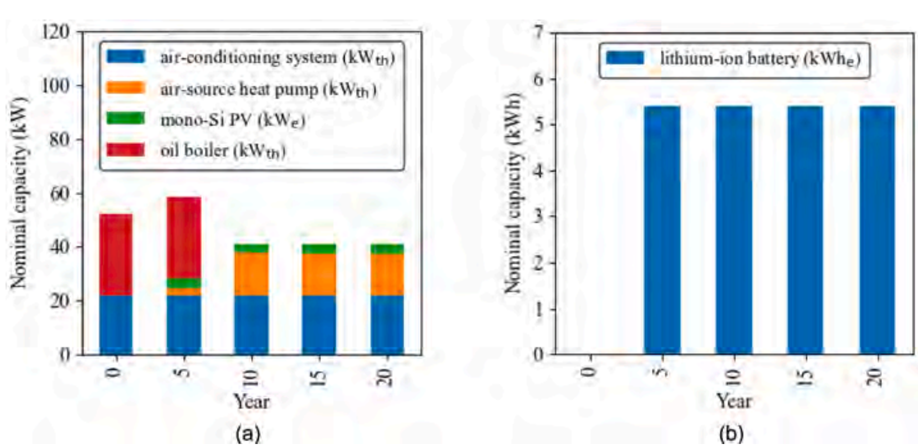


**Fig. 7.** Results of Optimised Case 1 for installed: (a) nominal power capacity of energy generation and conversion technologies, and (b) nominal energy capacity of energy storage technologies.

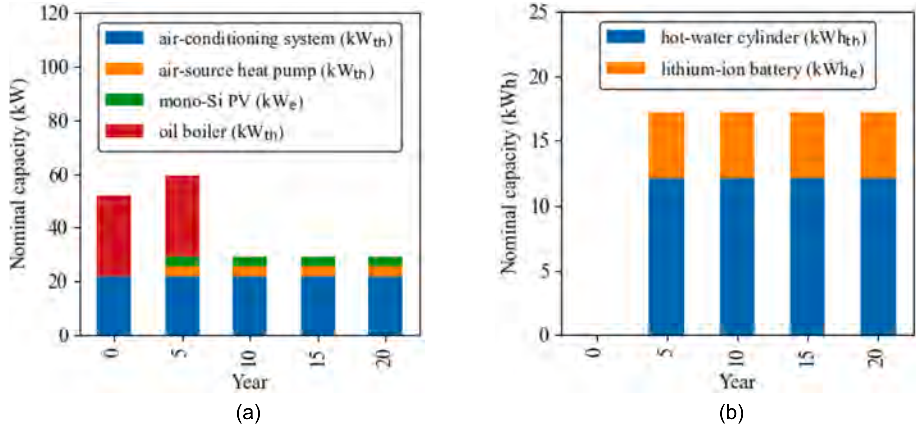


**Fig. 8.** Results of Optimised Case 2 for installed: (a) nominal power capacity of energy generation and conversion technologies, and (b) nominal energy capacity of energy storage technologies.

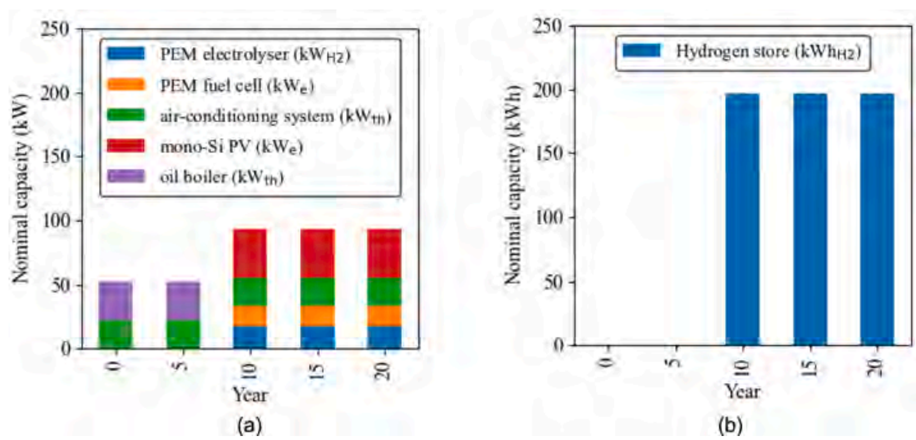


**Fig. 9.** Results of Optimised Case 3 for installed: (a) nominal power capacity of energy generation and conversion technologies, and (b) nominal energy capacity of energy storage technologies.

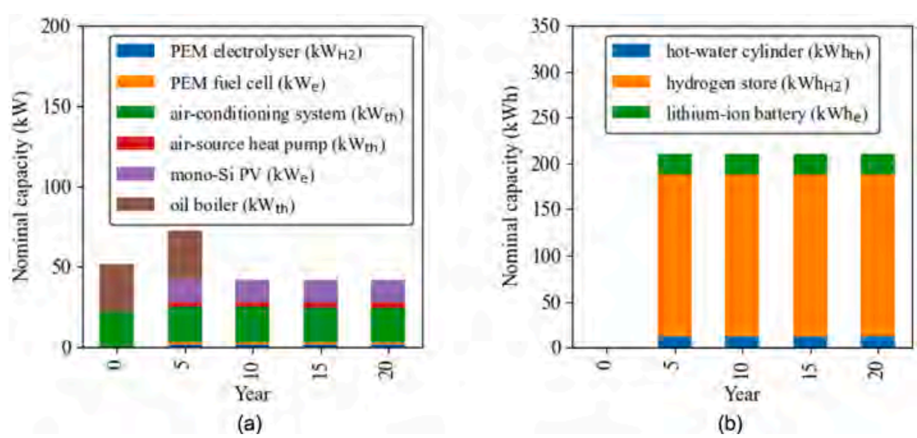


**Fig. 10.** Results of Optimised Case 4 for installed: (a) nominal power capacity of energy generation and conversion technologies, and (b) nominal energy capacity of energy storage technologies.

To achieve this, contours are used to show how the optimal size of each considered technology as obtained from the DO-IT framework changes for different electrolyser and battery prices in Fig. 14 and Fig. 15, and different electricity and heating demands in Fig. 16 and Fig. 17.

The price of importing electricity is fixed at 0.27 EUR/kWh$_e$ for Fig. 14 and Fig. 16, which is equal to the current average in Cyprus using the two-rate commercial and industrial tariff. In Fig. 15 and Fig. 17, the price of importing electricity is assumed to be double that of Fig. 14 and Fig. 16 (average price of 0.54 EUR/kWh$_e$), which is more representative of price conditions in other countries. Like the previous optimisation exercises, electricity exports and PV curtailment are not allowed.

The choice of specifically varying the electrolyser and battery prices in Fig. 14 and Fig. 15 is based on the fact that these two technologies are associated with the highest costs related to storing energy in the form of electricity and hydrogen, therefore the main synergies and trade-offs can be captured by varying these two parameters. Furthermore, given the

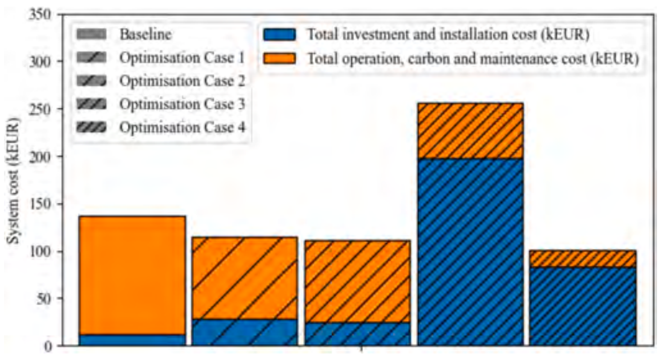


**Fig. 11.** Total investment and installation cost, and total operation, carbon and maintenance cost for the baseline case and the four technology availability optimisation cases described in Table 3.

**Table 4**
Aggregated annual energy generation for the different combinations of available technologies at the end of the 20-year planning horizon.

| Case | Annual electricity generation ($kWh_e$) | Annual heat generation ($kWh_{th}$) | Annual cold generation ($kWh_{th}$) | Annual hydrogen generation ($kWh_{H2}$) |
|---|---|---|---|---|
| Baseline Case (fuel oil boiler) | 0 | 10,400 | 17,800 | 0 |
| Optimised Case 1 (PV + ATWHP + battery) | 5,740 | 10,400 | 17,800 | 0 |
| Optimised Case 2 (PV + ATWHP + battery + hot water cylinder) | 5,810 | 10,600 | 17,800 | 0 |
| Optimised Case 3 (PV + electrolyser + $H_2$ storage + fuel cell CHP) | 52,900 | 10,400 | 17,800 | 26,000 |
| Optimised Case 4 (All options available) | 23,500 | 10,600 | 17,800 | 3200 |

**Table 5**
Aggregated annual energy imports and self-sufficiency for the combinations of available technologies at the end of the 20-year planning horizon.

| Case | Annual electricity imports ($kWh_e$) | Annual oil imports ($kWh_f$) | Self-sufficiency at end of horizon (%) |
|---|---|---|---|
| Baseline Case (fuel oil boiler) | 20,700 | 13,000 | 0.00% |
| Optimised Case 1 (PV + ATWHP + battery) | 17,000 | 0 | 25.3% |
| Optimised Case 2 (PV + ATWHP + battery + hot water cylinder) | 17,000 | 0 | 25.6% |
| Optimised Case 3 (PV + electrolyser + $H_2$ storage + fuel cell CHP) | 2,400 | 0 | 94.6% |
| Optimised Case 4 (All options available) | 3,300 | 0 | 90.6% |

absence of cold storage technologies in this study, there is no rationale for varying the cooling demand in Fig. 16 and Fig. 17. Changes in the cooling demand would only have a direct impact on electricity demand, a parameter that is already subject to variation. It is important to note that while the demand for electricity and heat are varied, these demand changes are applied to the hourly normalised profiles of the FOSS Living Lab. The lab serves as a valuable representative case study for office buildings, but the obtained sizes may not be directly applicable to other building types.

### 3.4.1. The role of battery and electrolyser prices

The influence of electrolyser and battery costs on technology adoption is evident in Fig. 14 and Fig. 15, particularly for the electrolyser and the battery, but also for the PVs and hydrogen storage systems that rely on these components. At lower grid electricity import prices (Fig. 14), the capacities of the battery, electrolyser, PVs, and hydrogen storage are shown to increase from 0 to 30 $kWh_e$, 0 to 3 $kW_{H2}$, 3 to 18 $kW_e$ and 0 to 300 $kWh_{H2}$, respectively, as electrolyser and battery prices decrease from 8000 to 3000 EUR/$kW_{H2}$ and 1000 to 250 EUR/$kWh_e$, respectively. The rationale behind these fluctuations is that, when electrolyser and battery costs are high, it is often more economical to buy electricity from the grid rather than investing in the decentralised collection and storage of renewable energy. Conversely, as the prices of electrolyser and batteries decrease, locally produced electricity becomes a more cost-effective option, reducing reliance on fluctuating grid electricity prices. The impact on heat pumps and hot-water cylinders differs, with their capacities showing some relatively small increase as electricity and hydrogen technology prices rise. This is attributed to the fact that, as the cost of storing energy in the form of electricity and hydrogen increases, a shift towards prioritising energy storage in the form of heat becomes more sensible.

At high grid electricity import prices (Fig. 15), a comparable pattern emerges regarding the impact of electrolyser and battery costs on PV and hydrogen storage capacities. Notably, in contrast to the low grid electricity import prices (Fig. 14), PVs and hydrogen storage are still installed even when electrolyser and battery prices are high. The minimum PV and hydrogen storage capacities are around 10 $kW_e$ and 200 $kWh_{H2}$, respectively. The heat pump and hot-water cylinder capacities are either unaffected or slightly increased when battery and electrolyser prices increase.

A comparative analysis of Fig. 14 and Fig. 15 reveals a distinct variation in the observed trend for electrolyser and battery capacities. In the scenario with high grid electricity prices (Fig. 15), there is a general inclination for their capacities to increase with declining technology costs, but evidently, there is a trade-off between opting for a high capacity of electrolyser or opting for a high capacity of battery. This trade-off is highly dependent on the specific costs of these two technologies. At the maximum battery-specific price (1000 EUR/$kWh_e$), for example, as the electrolyser price increases from 3000 to 8000 EUR/$kW_{H2}$, the battery capacity increases from 6 to 18 $kWh_e$ and the electrolyser capacity reduces from 4 to 2 $kW_{H2}$. This demonstrates the significance of using holistic approaches that capture interactions between all energy vectors when making technology investment decisions.

### 3.4.2. The role of building electricity and heat demand

Some interesting observations regarding the role of electricity and heat demand on the technology choices can be made from Fig. 16 and Fig. 17. At the low importing electricity price (Fig. 16), the capacities of PVs, the battery, the electrolyser and hydrogen storage are shown to be very limited for annual electricity demands lower than around 40 $MWh_e$. This is driven by the high investment price required for batteries and electrolysers. For the installation of these technologies to be cost-effective, there should be sufficient potential for operational cost savings during their lifetime.

In the low electricity price scenarios (Fig. 16), the nominal capacity of installed PVs is shown to vary between 0 and 80 $kW_e$ for different

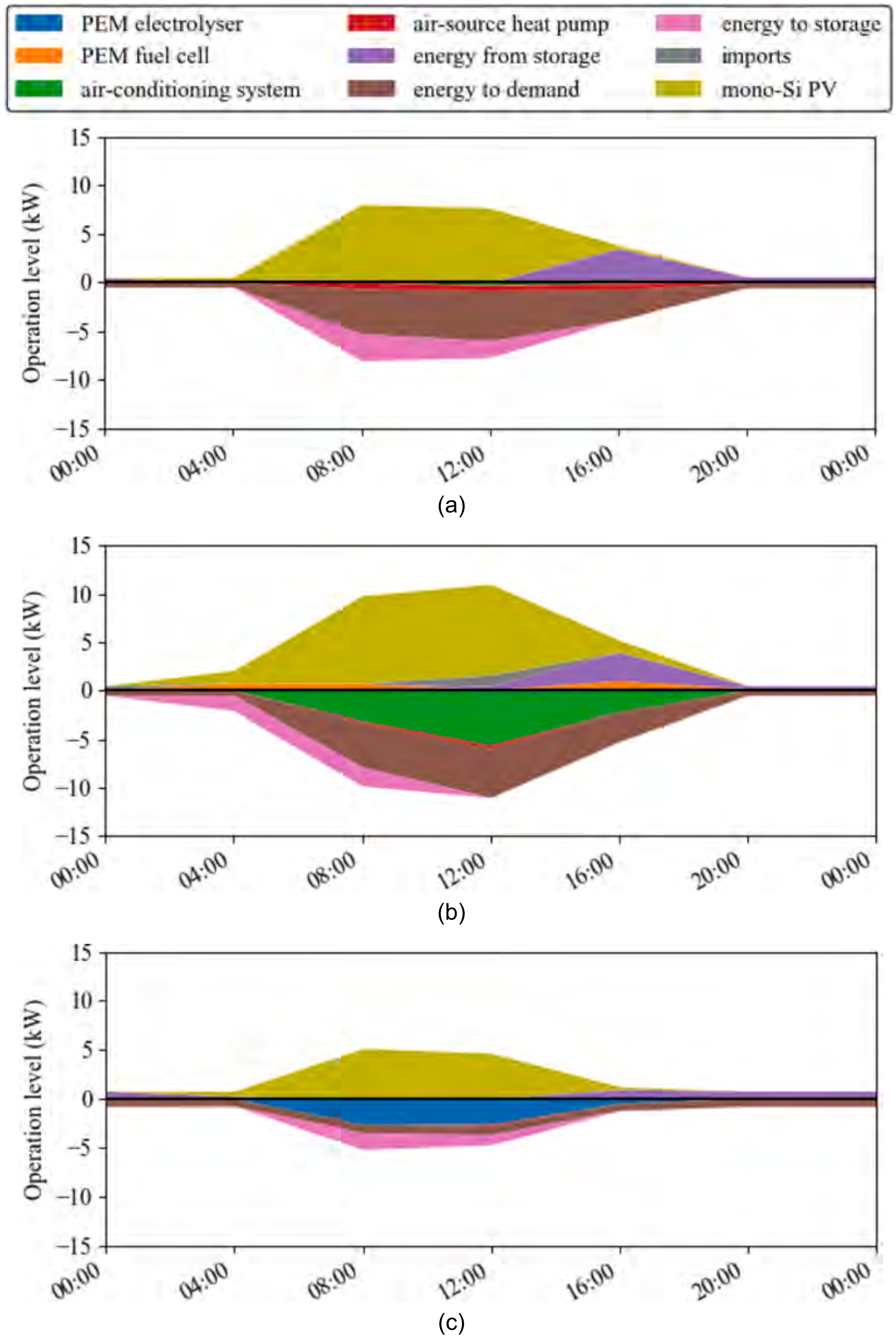


**Fig. 12.** Hourly operation of electricity generation ($kW_e$), use and storage technologies for Optimised Case 4 (which involves all technology options) for (a) a typical working day with a small amount of heating demand and high electricity prices in the afternoon, (b) a typical working day with high cooling demand and high electricity prices in the afternoon, and (c) a typical cold weekend day with negligible demand. Positive values indicate electricity generation and negative values indicate electricity use.

electricity and heat demands, while the associated battery capacity varies between 0 and 120 $kWh_e$. In the high electricity price scenarios (Fig. 17), PV and battery systems become cost-effective even at low electricity demands, and thus the optimal sizes never drop below 20 $kW_e$ and 20 $kWh_e$, respectively. As expected, changes in annual electricity demand largely affect optimal PV and battery sizes. At the same time, changes in heat demand also affect the sizing of the two systems, as heat is electrified through electricity-driven heat pumps, and a higher demand for heat generated by electricity results in higher PV and battery capacity requirements. The role of heat demand on the PV and battery capacities becomes even more evident in the higher electricity price scenarios (Fig. 17), showing that as the price of electricity increases, a higher degree of the electricity required for heating, is produced locally rather than being imported.

The annual heat demand is the main driver for the heat pump and hot-water cylinder capacities. The former varies between 5 and 40 $kW_{th}$ and the latter between 5 and 120 $kWh_{th}$ for annual heat demand variations in the range of 10–100 $MWh_{th}$. The demand for electricity also influences the heat pump and cylinder capacities at low electricity prices (Fig. 16). In fact, the hot-water cylinder optimal sizes are shown to drop after a certain annual electricity demand value, which is because a higher electricity demand results in higher battery capacities which can

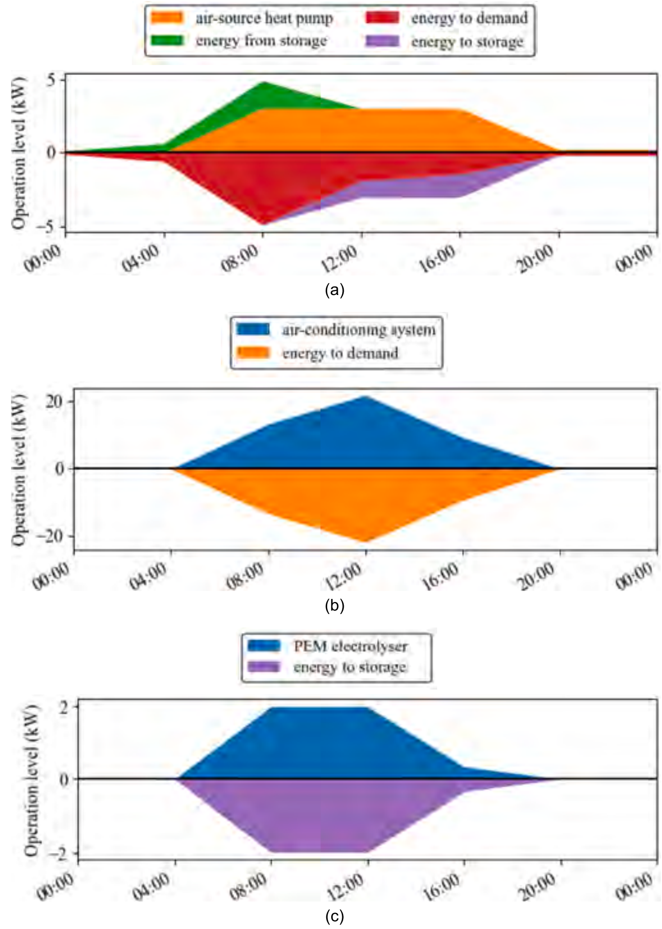


**Fig. 13.** Hourly operation for Optimised Case 4 (which involves all technology options) of (a) heating technologies for a typical working day with a small amount of heating demand and high electricity prices in the afternoon, (b) cooling technologies for a typical working day with high cooling demand and high electricity prices in the afternoon, and (c) hydrogen technologies for a typical cold weekend day with negligible demand. Positive values indicate energy generation and negative values indicate energy use.

sometimes be used to store electricity for heat, thus reducing the hot-water cylinder size requirements. This demonstrates the interlinks between electricity and heat vectors. When the price of imported electricity is high (Fig. 17), storing heat in the form of electricity in batteries becomes ineffective, and thus the heat pump and hot-water cylinder sizes are shown to almost solely depend on the heat demand.

The results of this analysis show that, in several demand and price scenarios, green hydrogen can have a notable role to play as a seasonal energy storage method in buildings. Although the nominal capacities of the electrolyser and hydrogen store are low at low electricity demands (below 2 $kW_{H2}$ and 100 $kWh_{H2}$, respectively), an increasing role of green hydrogen emerges as heat and electricity demands increase. The most interesting result is found in the high electricity price scenarios (Fig. 17), with hydrogen being found to store energy that is later converted to both electricity and heat. Since the considered fuel cell is a CHP system that can simultaneously provide electricity and heat, the optimal sizing of green hydrogen generation and storage technologies is a function of both energy vectors. As shown in Fig. 17(f), when heat and electricity demand approach 100 $MWh_{th}$ and 100 $MW_e$, respectively, optimal electrolyser and hydrogen storage capacities are as high as 10 $kW_{H2}$ and 3000 $kWh_{H2}$, respectively, showing the potential of hydrogen seasonal energy storage, a trend that may attract increasing attention in the upcoming years.

### 3.5. Key points, limitations and sensitivity to changing conditions

The results of this study demonstrate how various multi-energy-vector technologies can work together synergistically within buildings. Summarised below are the key findings, all of which have been quantified for different scenarios in Sections 3.2–3.4:

- Efficiently sizing and integrating electricity, heating, cooling, and hydrogen generation and storage technologies can lead to the lowest-cost transition towards achieving net-zero energy buildings.
- Batteries are effective in balancing intra-day fluctuations in demand and supply, while hot-water cylinders manage peak heating-demand periods effectively using a small heat pump capacity.
- Hydrogen storage primarily functions to store excess generated energy, with a small electrolyser producing hydrogen steadily at low capacity using electricity from batteries.
- During periods of high electricity and heat demand, fuel cells can efficiently generate electricity and heat at a steady low capacity, which can be stored in batteries and hot-water cylinders for later use.
- Decreasing prices of electrolyser and batteries make locally produced electricity a more cost-effective option. In certain circumstances, high prices of these technologies may lead to prioritising thermal energy storage.
- The decision between investing in a high-capacity electrolyser or a high-capacity battery depends primarily on technology prices rather than resource prices.
- Changes in heat demand not only impact the requirements for heat pumps and hot-water cylinders but also influence the sizes of PV systems and batteries since heat is produced using electricity.
- High electricity demand may necessitate large battery capacities, which can also serve for electricity storage for heating, potentially reducing the requirement for large-scale hot-water cylinders.
- The optimal sizing of green hydrogen generation and storage technologies depends on both electricity and heat demand.

The study also has several limitations. Optimisation models that are used to identify long-term energy design and operation strategies often oversimplify building energy demand and technology performance and cost, especially of heating and cooling systems. To address this, the DO-IT framework mitigated these limitations by integrating building energy demand, technology modelling, and energy system optimisation, reducing uncertainties related to buildings and technologies. However, this study primarily focuses on defining and utilising the generic technology design and operation optimisation model. Although the DO-IT framework can account for how different building design choices impact energy demand, factors such as materials, occupancy patterns, passive design considerations and energy efficiency measures were not included in the scope of this study. In fact, the building construction, occupancy and operation can impact thermal interactions and performance and thus influence the technology selection of the modelling tool. These aspects will be addressed in subsequent studies.

Furthermore, the case study conducted in this work was based on an office building, and as such, the findings do not directly apply to other types of buildings. Future analyses will investigate the specific impact of building parameters on demand profiles, in an effort to facilitate the identification of optimal trade-offs between technology selection for various residential, commercial and industrial environments.

In order to characterise technology cost and performance characteristics in this study, we have used detailed models and libraries that combine data from various manufacturers whenever possible, instead of relying on single values. However, the data used are still susceptible to significant uncertainties. Building demand is influenced by various design factors, while technology and resource prices are subject to shifts in demographics, economics, and technology, making precise estimates challenging. Such uncertainties are a common challenge in energy system optimisation and planning models. At the same time, as technology

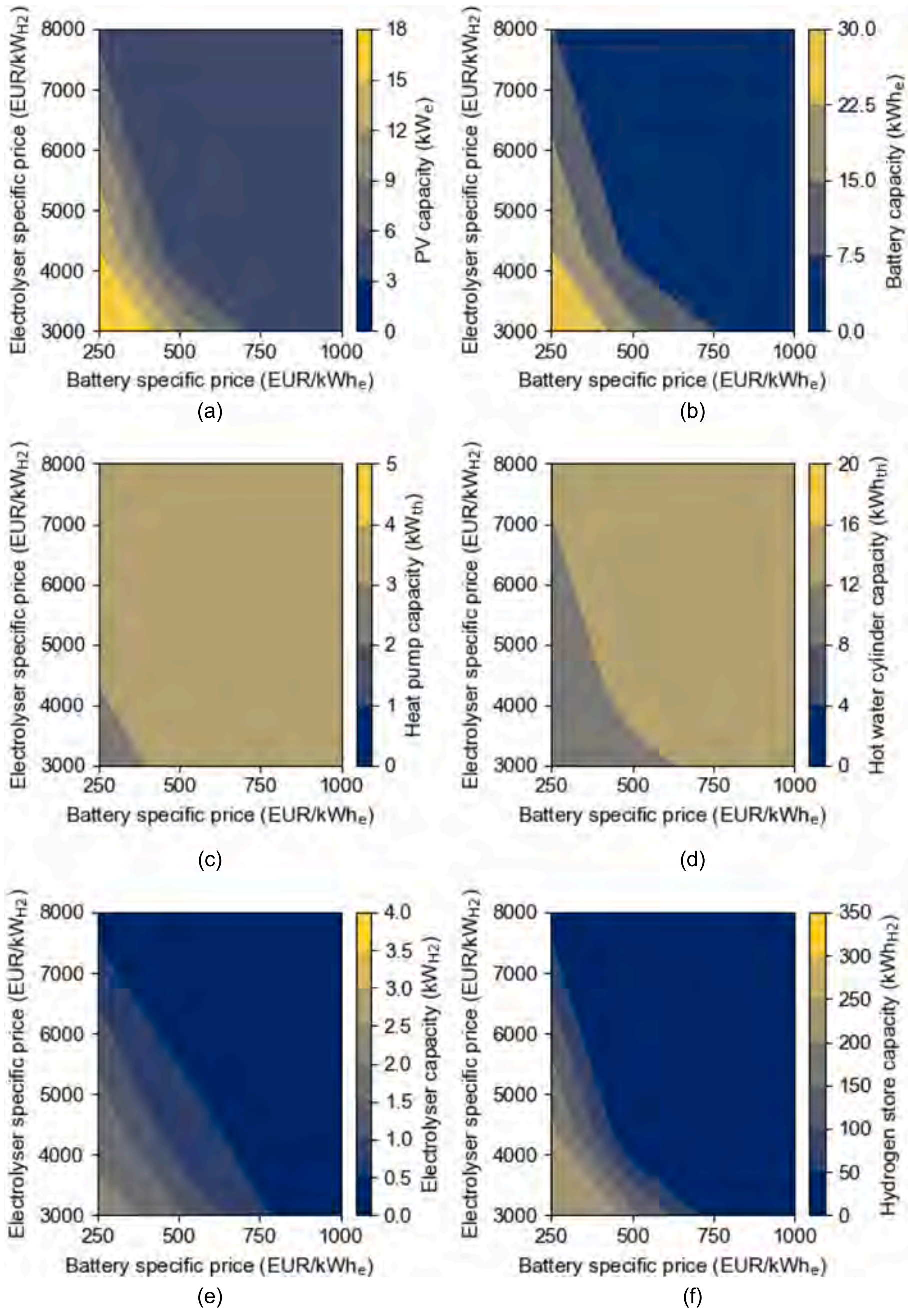


**Fig. 14.** Optimal size of technologies obtained using the DO-IT framework for varying electrolyser and battery specific prices. The price of importing electricity is here fixed at 0.27 EUR/kWh$_e$: (a) mono-Si PV, (b) lithium-ion battery, (c) ATWHP, (d) hot-water cylinder, (e) electrolyser, and (f) hydrogen store.

scales up, significant economies of scale can emerge, affecting cost modelling. Since the case study was based on a small-office application, cost estimates were based on relatively small energy generation and conversion capacities (0–20 kW) and energy storage capacities (0–20 kWh). It is also important to note that the optimised hydrogen infrastructure results assume that PV curtailment and electricity exports should be avoided. If PV electricity could be exported or curtailed, installing larger PV systems and smaller hydrogen infrastructure might have been another cost-effective option.

The results indicate that the choice of using average specific prices for technologies within the aforementioned ranges was adequate, as optimal technology sizes mostly fall within these ranges, except for some technologies in the high-demand scenarios of Section 3.4. However, it is important to state that even within the aforementioned ranges, economies of scale are evident; for example, a 3 kW$_{th}$ heat pump has a higher specific cost than a 10 kW$_{th}$ heat pump. While our model does not impose a size limitation, selecting higher capacities may overlook some economies of scale. Overall, we recognise that the costs and capacities provided by the DO-IT framework are estimated indicators and not precise numerical values. In future studies, instead of assuming a specific price for each technology, we intend to apply different prices based on size ranges (e.g., 0–5 kW, 5–10 kW, 10–15 kW, 15–20 kW), an approach that has the potential to improve accuracy, particularly when applied to buildings of varying sizes and types.

In an effort to mitigate the inherent uncertainties in the developed model, we conducted an analysis in Section 3.4 to show how the optimal size of the main considered technologies varies across different demand, technology price, and electricity price scenarios. This analysis showed the sensitivity of technology sizes to these factors. Fig. 18 presents the capacity ranges for these technologies in all examined scenarios,

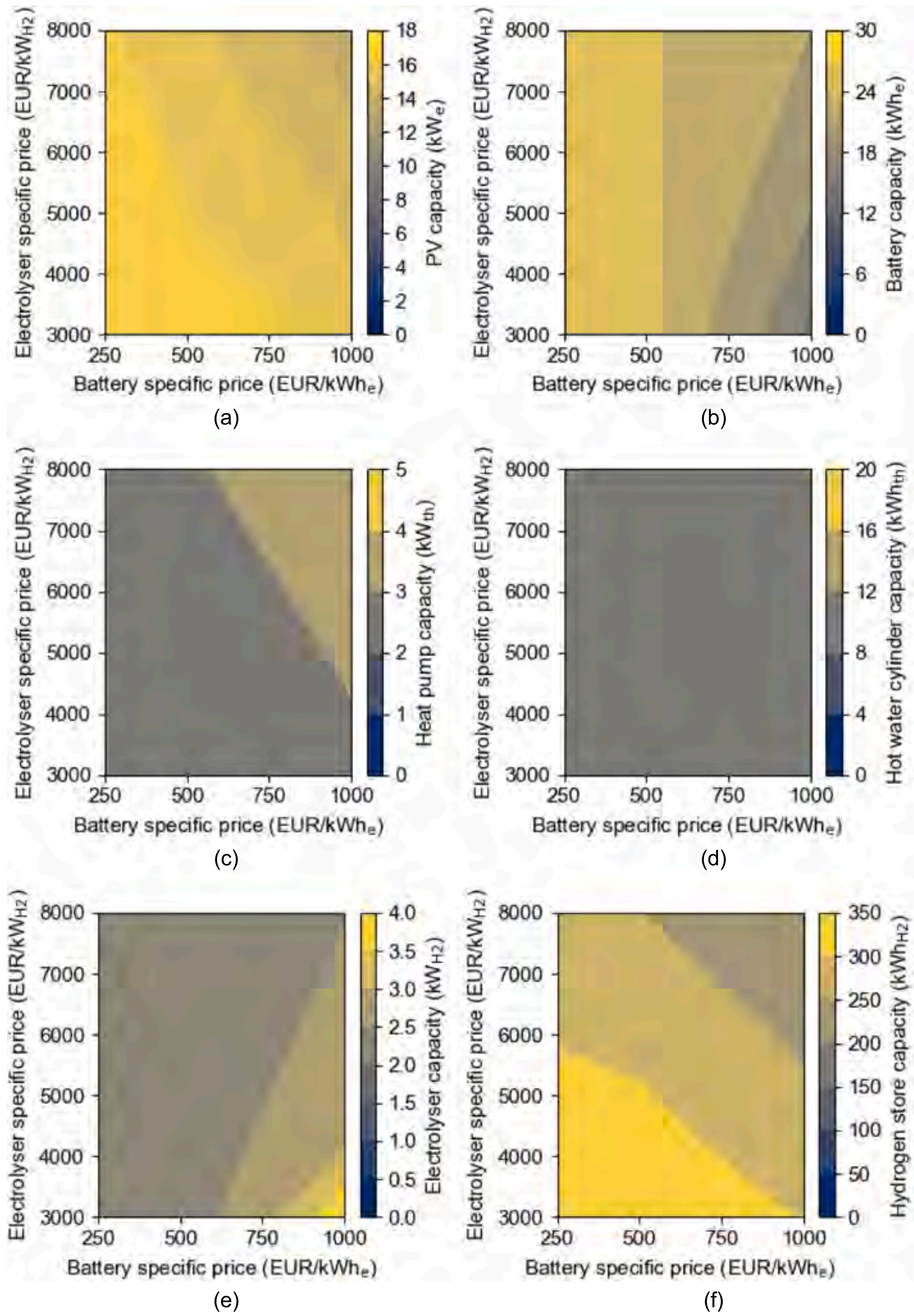


**Fig. 15.** Optimal size of technologies obtained using the DO-IT framework for varying electrolyser and battery specific prices. The price of importing electricity is here fixed at 0.54 EUR/kWh$_e$: (a) mono-Si PV, (b) lithium-ion battery, (c) ATWHP, (d) hot-water cylinder, (e) electrolyser; and (f) hydrogen store.

demonstrating their variability in response to changing conditions.

Despite the uncertainties arising from building demand, technology cost and performance, and resource price assumptions, the importance of integrating PV systems with multiple forms of energy storage is evident in Fig. 18. Notably, the heat pump capacity only shows a modest variation between approximately 3–35 kW$_{th}$, while the electrolyser experiences an even narrower range between 0 and 9 kW$_{H2}$. In contrast, electrochemical, thermal, and hydrogen storage systems can reach capacities exceeding 100 kWh depending on the scenario. This highlights the tendency of the optimisation model to minimise the required capacities of heating and hydrogen generation technologies, which involve significant investment costs. Through smart control strategies, thermal and hydrogen storage can effectively complement batteries without the need for large heat pump and electrolyser systems.

## 4. Conclusions

The integration of renewable energy sources into the electricity, heating, and cooling technologies of buildings is a field of increasing attention due to the complicated interactions among various technology options within multi-energy-vector systems. Implementing effective solutions necessitates intelligent energy system design and control. This study involved the development of the Design and Operation of Integrated Technologies (DO-IT) framework, a novel tool that holds the potential to provide insights for guiding short- and long-term technology investment and operation strategies for buildings. The framework brings together advanced open-source tools to model the building energy demand, the technology cost and performance and the energy system design and operation optimisation, thus identifying synergies, trade-offs, and interdependencies between different energy processes

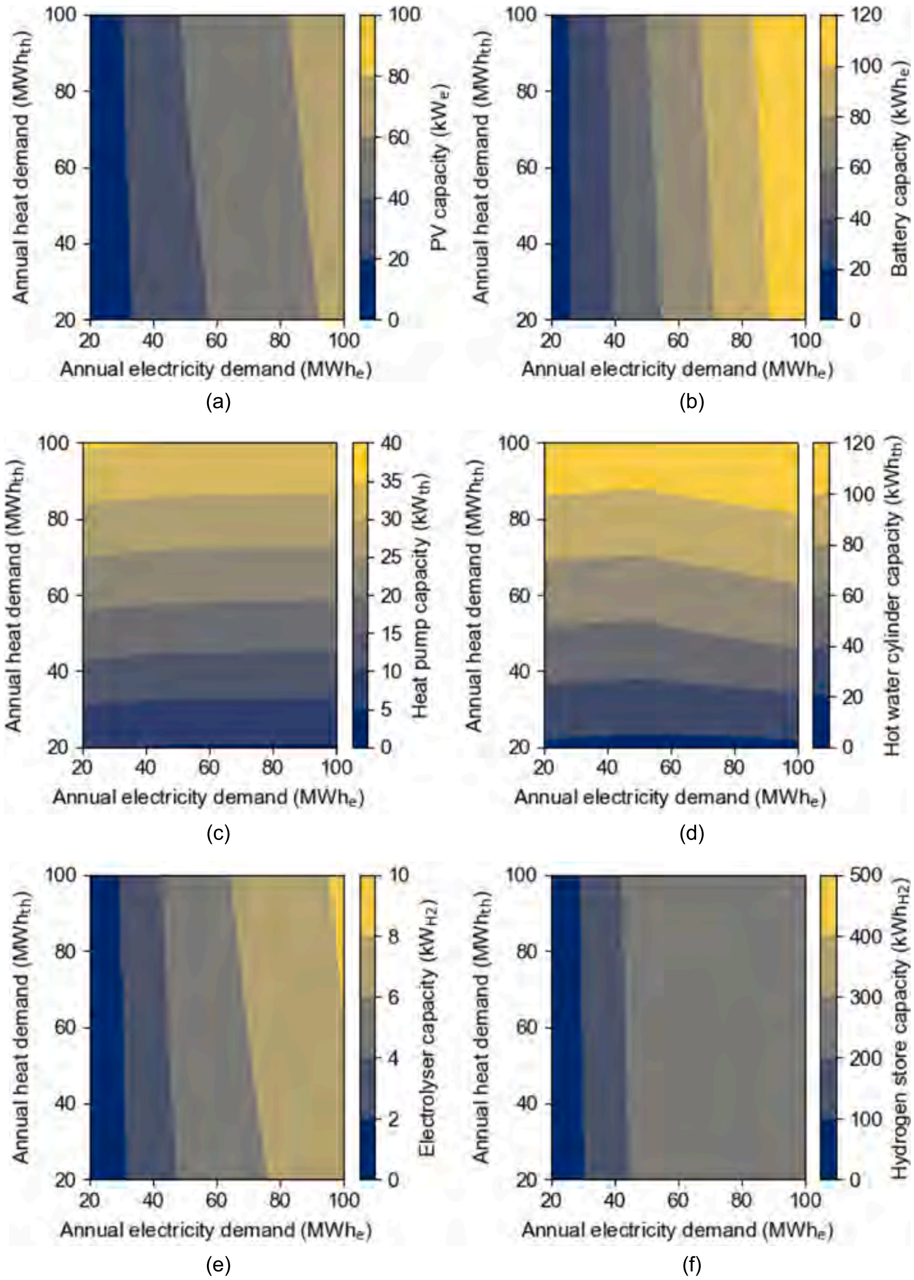


**Fig. 16.** Optimal size of technologies obtained using the DO-IT framework for varying annual heat and electricity demands. The price of importing electricity is here fixed at 0.27 EUR/$kWh_e$: (a) mono-Si PV, (b) lithium-ion battery, (c) ATWHP, (d) hot-water cylinder, (e) electrolyser, and (f) hydrogen store.

(generation, conversion, storage) and vectors (electricity, heat, cold and hydrogen).

The DO-IT framework was here used to identify the optimal mix of technologies and optimal timing at which electricity, heat and hydrogen should be produced, stored, and used for an office building at the University of Cyprus, representing how technologies can interact within typical office buildings. The objective was to identify the future technology portfolio that minimises the total system cost (sum of investment, installation, operation, carbon and maintenance costs) for a planning horizon of 20 years. Following a detailed modelling approach to acquire electricity, heating and cooling demand profiles for the office spaces based on the building attributes (work schedules, construction, lightning systems and usage of equipment), the DO-IT framework was used to define strategies for different combinations of technologies being assumed to be available for installation and operation: (i) a PV-electric heat pump-battery system, (ii) a PV-electric heat pump-battery-thermal storage system, (iii) a PV-electrolyser-hydrogen storage-fuel cell system, and (iv) a system with all above technology options. The different optimised results were compared to a baseline system that assumes that electricity and heat demand are met using electricity from the grid and a fuel oil boiler, respectively.

The findings indicated that integrating all electricity, heating, and hydrogen generation and storage technologies resulted in the minimum total system cost. Specifically, the total system cost was in this case equal to 101,000 EUR, which was 26% lower than the baseline scenario. Moreover, this integrated system achieved a high self-sufficiency rate of 91%. Of particular interest is the synergistic installation of various energy storage methods: electrical, thermal, and hydrogen. The battery effectively mitigates intra-day fluctuations, while thermal energy storage enables efficient management of peak-heating-demand periods using a compact heat pump unit. Hydrogen energy storage emerges as a strategic solution for storing excess energy during periods of high PV

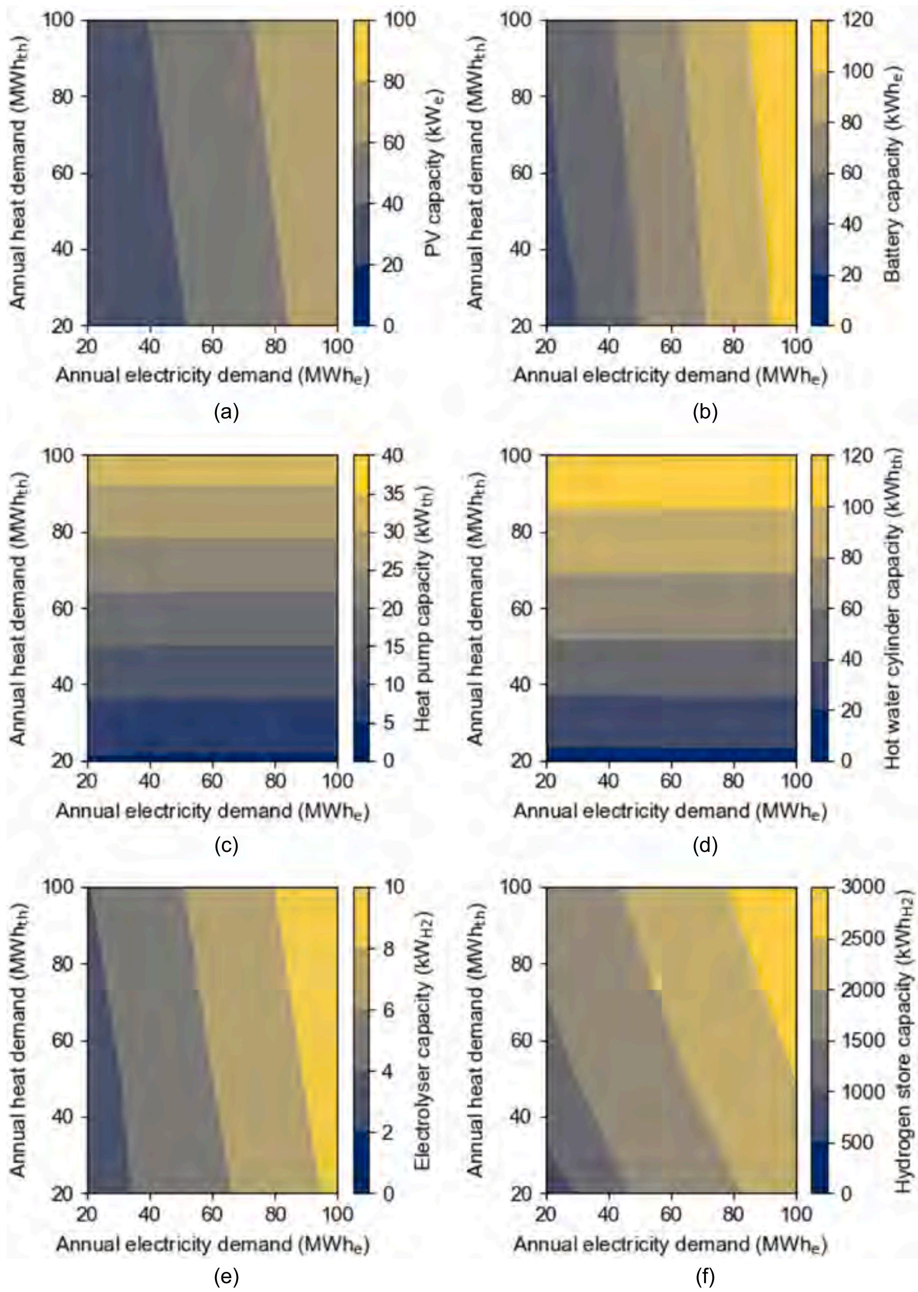


**Fig. 17.** Optimal size of technologies obtained using the DO-IT framework for varying annual heat and electricity demands. The price of importing electricity is here fixed at 0.54 EUR/kWh$_e$: (a) mono-Si PV, (b) lithium-ion battery, (c) ATWHP, (d) hot-water cylinder, (e) electrolyser, and (f) hydrogen store.

generation, spanning days, weeks, or even seasons.

Following the case study analysis, an examination of how the size of each considered technology in this work changes for varying electrolyser and battery prices, electricity and heating demands, as well as fluctuating electricity prices, was conducted. The optimal sizing of all electricity, heating, and hydrogen generation and storage technologies – comprising PV, battery, heat pump, hot-water cylinder, electrolyser, and hydrogen store – was shown to be influenced by both technology prices and energy demand fluctuations. This demonstrates the interdependencies between electricity, heating, cooling and hydrogen technologies, emphasising the critical importance of simultaneously optimising investments across different energy vectors.

The generic nature of the DO-IT framework enables the modelling of interactions among diverse energy vectors, technologies and buildings. Based on this, future work will concentrate on two key areas: (i) refining the modelling methodology to better address uncertainties in decision-making processes and to accurately represent technology and building attributes, and (ii) broadening the framework application to building contexts beyond the current case study. In addressing the first aspect, efforts will focus on incorporating stochastic methodologies to account for modelling uncertainties. This will enable stakeholders to make informed investment and operational decisions by considering the probabilistic nature of future prices and technological advancements. Furthermore, accounting for technological learning from the extended deployment of certain technologies, which is likely to reduce prices in the future, as well as technology degradation, will provide valuable insights into the long-term performance and cost-effectiveness of technology options. The second aspect involves analysing and comparing technology investment and operation strategies for different building types, including residential, commercial, and industrial buildings, each with unique energy demands influenced by distinct characteristics and occupant behaviours. This will involve detailed comparisons of building

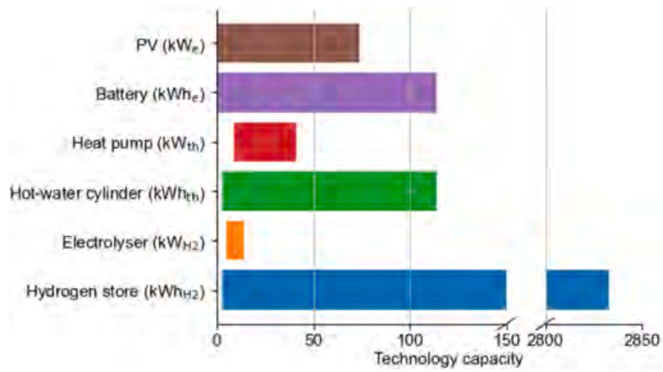


**Fig. 18.** Sensitivity analysis showing the ranges of potential technology capacities across various scenarios of battery and electrolyser prices, electricity prices, and building electricity and heat demands.

design and retrofit choices (e.g., construction, energy efficiency measures) with optimal technology selection and operation. Lastly, the scope of the work will be extended to integrated configurations within smart energy campuses and communities, where buildings can act as consumers but also share energy among them. This extension will offer opportunities to enhance resilience and promote the energy autonomy of energy communities.

## CRediT authorship contribution statement

**Andreas V. Olympios:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Fanourios Kourougianni:** Writing – original draft, Methodology, Investigation, Formal analysis. **Alexandros Arsalis:** Writing – original draft, Methodology, Formal analysis, Data curation. **Panos Papanastasiou:** Writing – review & editing, Supervision, Investigation, Formal analysis. **Antonio M. Pantaleo:** Writing – review & editing, Investigation, Formal analysis. **Christos N. Markides:** Writing – review & editing, Supervision, Investigation. **George E. Georghiou:** Writing – review & editing, Supervision, Resources, Project administration, Investigation.

## Declaration of competing interest

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

## Data availability

Data will be made available on request.

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## References

[1] Green MA. Photovoltaic technology and visions for the future. Progress Energy 2019;1:013001.
[2] Roga S, Bardhan S, Kumar Y, Dubey SK. Recent technology and challenges of wind energy generation: a review. Sustain Energy Technol Assess 2022;52:102239.
[3] European Commission. An EU strategy on heating and cooling. https://energy.ec.europa.eu/topics/energy-efficiency/heating-and-cooling_en; 2016.
[4] Lamnatou C, Chemisana D, Cristofari C. Smart grids and smart technologies in relation to photovoltaics, storage systems, buildings and the environment. Renew Energy 2022;185:1376–91.
[5] International Energy Agency. Heating and cooling strategies in the clean energy transition. https://www.iea.org/reports/heating-and-cooling-strategies-in-the-clean-energy-transition; 2019.
[6] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy 2010;87(4):1059–82.
[7] Ferrari S, Zagarella F, Caputo P, Bonomolo M. Assessment of tools for urban energy planning. Energy 2019;176:544–51.
[8] Olympios AV, Aunedi M, Mersch M, Krishnaswamy A, Stollery C, Pantaleo AM, et al. Delivering net-zero carbon heat: Technoeconomic and whole-system comparisons of domestic electricity- and hydrogen-driven technologies in the UK. Energy Convers Manag 2022;262:115649.
[9] Olympios AV, Sapin P, Freeman J, Olkis C, Markides CN. Operational optimisation of an air-source heat pump system with thermal energy storage for domestic applications. Energy Convers Manag 2022;273:116426.
[10] Peng J, Lu L. Investigation on the development potential of rooftop PV system in Hong Kong and its environmental benefits. Renew Sust Energ Rev 2013;27:149–62.
[11] Alshahrani A, Omer S, Su Y, Mohamed E, Alotaibi S. The technical challenges facing the integration of small-scale and large-scale PV systems into the grid: a critical review. Electronics 2019;8(12):1443.
[12] United Nations Environment Program. Global status report for buildings and construction. 2022.
[13] O'Shaughnessy E, Cruce JR, Xu K. Too much of a good thing? Global trends in the curtailment of solar PV. Sol Energy 2020;208:1068–77.
[14] Bird L, Lew D, Milligan M, Carlini EM, Estanqueiro A, Flynn D, et al. Wind and solar energy curtailment: a review of international experience. Renew Sust Energ Rev 2016;65:577–86.
[15] Perez M, Perez R, Rábago KR, Putnam M. Overbuilding & curtailment: the cost-effective enablers of firm PV generation. Sol Energy 2019;180:412–22.
[16] Segundo Sevilla FR, Parra D, Wyrsch N, Patel MK, Kienzle F, Korba P. Techno-economic analysis of battery storage and curtailment in a distribution grid with high PV penetration. J Energy Storage 2018;17:73–83.
[17] Spertino F, Fichera S, Ciocia A, Malgaroli G, Di Leo P, Ratclif A. Toward the complete self-sufficiency of an NZEBS microgrid by photovoltaic generators and heat pumps: methods and applications. IEEE Trans Ind Appl 2019;55(6):7028–40.
[18] Saheb Y, Shnapp S, Paci D. From nearly-zero energy buildings to net-zero energy districts: Lessons learned from existing EU projects. 2019. https://publications.jrc.ec.europa.eu/repository/handle/JRC115188.
[19] International Energy Agency. The future of heat pumps. Technical report. https://www.iea.org/reports/the-future-of-heat-pumps; 2022.
[20] Hoseinpoori P, Olympios AV, Markides CN, Woods J, Shah N. A whole-system approach for quantifying the value of smart electrification for decarbonising heating in buildings. Energy Convers Manag 2022;268:115952.
[21] Olabi AG, Onumaegbu C, Wilberforce T, Ramadan M, Abdelkareem MA, Al-Alami AH. Critical review of energy storage systems. Energy 2021;214:119897.
[22] Luo X, Wang J, Dooner M, Clarke J. Overview of current development in electrical energy storage technologies and the application potential in power system operation. Appl Energy 2015;137:511–36.
[23] Olympios AV, McTigue JD, Farres-Antunez P, Tafone A, Romagnoli A, Li Y, et al. Progress and prospects of thermo-mechanical energy storage – a critical review. Progress Energy 2021;3:022001.
[24] Arsalis A, Alexandrou AN, Georghiou GE. Thermoeconomic modeling of a completely autonomous, zero-emission photovoltaic system with hydrogen storage for residential applications. Renew Energy 2018;126:354–69.
[25] Crawley DB, Hand JW, Kummert M, Griffith BT. Contrasting the capabilities of building energy performance simulation programs. Build Environ 2008;43(4):661–73.
[26] U.S. Department of Energy. Building technologies program: Building energy software tools directory. https://www.energy.gov/eere/buildings/building-technologies-office; 2023. Accessed: November 2023.
[27] National Renewable Energy Laboratory. EnergyPlus 23.2.0. https://energyplus.net. [Accessed November 2023].
[28] Hirsch J. eQUEST: the QUick Energy Simulation Tool. https://www.doe2.com/equest. [Accessed November 2023].
[29] Thermal Energy System Specialists. TRNSYS: Transient system simulation tool. https://www.trnsys.com. [Accessed November 2023].
[30] Integrated Environmental Solutions. IES Virtual Environment: The leading integrated suite for accurate whole building performance simulation. https://www.iesve.com/software/virtual-environment; 2023. Accessed: November 2023.
[31] You M, Wang Q, Sun H, Castro I, Jiang J. Digital twins based day-ahead integrated energy system scheduling under load and renewable energy uncertainties. Appl Energy 2022;305:117899.
[32] Tziolis G, Livera A, Montes-Romero J, Theocharides S, Makrides G, Georghiou GE. Direct short-term net load forecasting based on machine learning principles for solar-integrated microgrids. IEEE Access 2023;11:102038–49.
[33] Al-janabi A, Kavgic M, Mohammadzadeh A, Azzouz A. Comparison of EnergyPlus and IES to model a complex university building using three scenarios: free-floating, ideal air load system, and detailed. J Build Eng 2019;22:262–80.
[34] Imam S, Coley DA, Walker I. The building performance gap: are modellers literate? Build Serv Eng Res Technol 2017;38(3):351–75.
[35] Zhu D, Hong T, Yan D, Wang C. A detailed loads comparison of three building energy modeling programs: EnergyPlus, DeST and DOE-2.1E. Build Simul 2013;6:323–35.

[36] Danish Energy Agency. Technology Data. https://ens.dk/en/our-services/projections-and-models/technology-data; 2023. Accessed: November 2023.
[37] National Renewable Energy Laboratory. Annual technology baseline. https://atb.nrel.gov. [Accessed November 2023].
[38] National Renewable Energy Laboratory. PVWatts Calculator. https://pvwatts.nrel.gov. [Accessed November 2023].
[39] Mongird K, Viswanathan V, Balducci P, Alam J, Fotedar V, Koritarov V, et al. Energy storage technology and cost characterization report. U.S. Department of Energy; 2019. https://energystorage.pnnl.gov/pdf/PNNL-28866.pdf.
[40] Olympios AV, Mersch M, Sapin P, Pantaleo AM, Markides CN. Library of price and performance data of domestic and commercial technologies for low-carbon energy systems. Zenodo 2021. https://doi.org/10.5281/zenodo.5758943. Version 1.02.
[41] Department for Business, Energy & Industrial Strategy. Hydrogen production costs. https://www.gov.uk/government/publications/hydrogen-production-costs-2021; 2021.
[42] Olympios AV, Song J, Ziolkowski A, Shanmugam VS, Markides CN. Data-driven compressor performance maps and cost correlations for small-scale heat-pumping applications. Energy 2024;291:130171.
[43] Olympios AV, Hoseinpoori P. Markides C.N.Toward optimal designs of domestic air-to-water heat pumps for a net-zero carbon energy system in the UK. Cell Reports Sustainability 2024;1(2):100021.
[44] Ringkjøb HK, Haugan PM, Solbrekke IM. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew Sust Energ Rev 2018;96:440–59.
[45] Lopion P, Markewitz P, Robinius M, Stolten D. A review of current challenges and trends in energy systems modeling. Renew Sust Energ Rev 2018;96:156–66.
[46] UL Solutions. HOMER Renewable Energy Microgrid Software. https://www.homerenergy.com/products/software.html. [Accessed November 2023].
[47] Cedillos Alvarado D, Acha S, Shah N, Markides CN. A technology selection and operation (TSO) optimisation model for distributed energy systems: mathematical formulation and case study. Appl Energy 2016;180:491–503.
[48] Schütz T, Schiffer L, Harb H, Fuchs M, Müller D. Optimal design of energy conversion units and envelopes for residential building retrofits using a comprehensive MILP model. Appl Energy 2017;185:1–15.
[49] Panagiotidou M, Aye L, Rismanchi B. Optimisation of multi-residential building retrofit, cost-optimal and net-zero emission targets. Energ Build 2021;252:111385.
[50] Jennings M, Fisk D, Shah N. Modelling and optimization of retrofitting residential energy systems at the urban scale. Energy 2014;64:220–33.
[51] Shen M, Tang B, Zhang K. Low carbon operation optimisation strategies for heating, ventilation and air conditioning systems in office buildings. Int J Prod Res 2024:1–20.
[52] Wang Y, Quan Z, Jing H, Wang L, Zhao Y. Performance and operation strategy optimization of a new dual-source building energy supply system with heat pumps and energy storage. Energy Convers Manag 2021;239:114204.
[53] Lindberg KB, Doorman G, Fischer D, Korpås M, Ånestad A, Sartori I. Methodology for optimal energy system design of zero energy buildings using mixed-integer linear programming. Energ Build 2016;127:194–205.
[54] Huang Z, Yu H, Peng Z, Zhao M. Methods and tools for community energy planning: a review. Renew Sust Energ Rev 2015;42:1335–48.
[55] Delangle A, Lambert RSC, Shah N, Acha S, Markides CN. Modelling and optimising the marginal expansion of an existing district heating network. Energy 2017;140:209–23.
[56] Mehleri ED, Sarimveis H, Markatos NC, Papageorgiou LG. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. Energy 2012;44:96–104.
[57] Wu R, Mavromatidis G, Orehounig K, Carmeliet J. Multiobjective optimisation of energy systems and building envelope retrofit in a residential community. Appl Energy 2017;190:634–49.
[58] Strbac G, Pudjianto D, Sansom R, Djapic P, Ameli H, Shah N, et al. Analysis of alternative UK heat decarbonisation pathways. Imperial College London; 2018.
[59] Bynum ML, Hackebeil GA, Hart WE, Laird CD, Nicholson BL, Siirola JD, et al. Pyomo - optimization modeling in Python. 3rd ed.vol. 67. Springer; 2021.
[60] Kotzur L, Markewitz P, Robinius M, Stolten D. Time series aggregation for energy system design: modeling seasonal storage. Appl Energy 2018;213:123–35.
[61] The pandas development team. Pandas Zenodo. 2020. https://doi.org/10.5281/zenodo.3509134.
[62] Hunter JD. Matplotlib: a 2D graphics environment. Comput Sci Eng 2007;9(3):90–5.
[63] Johari F, Munkhammar J, Shadram F, Widén J. Evaluation of simplified building energy models for urban-scale energy analysis of buildings. Build Environ 2022;211:108684.
[64] National Renewable Energy Laboratory. OpenStudio v3.5.1. https://openstudio.net; 2023.
[65] OpenStudio Coalition. OpenStudio Application v1.5.0. https://openstudiocoalition.org; 2023.
[66] National Renewable Energy Laboratory. PVWatts calculator. https://pvwatts.nrel.gov; 2023.
[67] Dobos AP. PVWatts v5 Manual. https://www.nrel.gov/docs/fy14osti/62641.pdf; 2014.
[68] Arsalis A, Kær SK, Nielsen MP. Modeling and optimization of a heat-pump-assisted high temperature proton exchange membrane fuel cell micro-combined-heat-and-power system for residential applications. Appl Energy 2015;147:569–81.
[69] DiOrio N, Dobos A, Janzou S, Nelson A, Lundstrom B. Technoeconomic modeling of battery energy storage in SAM. National Renewable Energy Laboratory; 2015. https://www.nrel.gov/docs/fy15osti/64641.pdf.
[70] Arsalis A, Alexandrou AN, Georghiou GE. A comparative review of lithium-ion battery and regenerative hydrogen fuel cell technologies for integration with photovoltaic applications. Renew Energy 2022;191:943–60.
[71] Arsalis A, Nielsen MP, Kær SK. Application of an improved operational strategy on a PBI fuel cell-based residential system for Danish single-family households. Appl Therm Eng 2013;50(1):704–13.
[72] Mersch M, Olympios AV, Sapin P, Mac Dowell N, Markides CN. Solar-thermal heating potential in the UK: A techno-economic whole-energy system analysis. In: The 34rth International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, 27 June 27–2 July, Taormina, Italy; 2021.
[73] Kotzur L, Markewitz P, Robinius M, Stolten D. Impact of different time series aggregation methods on optimal energy system design. Renew Energy 2018;117:474–87.
[74] Institute of Energy and Climate Research. Tsam - time series aggregation module. Forschungszentrum Jülich; 2021. https://tsam.readthedocs.io.
[75] American Society of Heating, Refrigerating and Air-Conditioning Engineers. Climatic data for building design standards. https://www.ashrae.org/file%20library/technical%20resources/standards%20and%20guidelines/standards%20addenda/169_2020_a_20211029.pdf; 2021.
[76] Lawrie L, Crawley DB. Development of global typical meteorological years (TMYx). https://climate.onebuilding.org. [Accessed November 2023].
[77] American Society of Heating, Refrigerating and AAir-Conditioning Engineers. International weather for energy calculations v2.0. https://www.ashrae.org/technical-resources/bookstore/ashrae-international-weather-files-for-energy-calculations-2-0-iwec2; 2011.
[78] Electricity Authority of Cyprus. Commercial and industrial use tariffs. 2022. https://www.eac.com.cy/EN/RegulatedActivities/Supply/tariffs/Documents/Commercial%20and%20Industrial%20Use_22-6-22.pdf.
[79] Global Petrol Prices. Cyprus fuel prices, electricity prices. https://www.globalpetrolprices.com/Cyprus; 2023.
[80] UK Department for Energy Security and Net Zero. Government conversion factors for company reporting of greenhouse gas emissions. https://www.gov.uk/government/collections/government-conversion-factors-for-company-reporting; 2022.
[81] Republic of Cyprus. Cyprus' integrated national energy and climate plan. https://energy.ec.europa.eu/system/files/2020-01/cy_final_necp_main_en_0.pdf; 2020.