Energy & Buildings 319 (2024) 114411

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

# Impact of temporal resolution on the design and reliability of residential energy systems

Olalekan Omoyele [a,b,*], Silvana Matrone [c], Maximilian Hoffmann [a], Emanuele Ogliari [c], Jann Michael Weinand [a], Sonia Leva [c], Detlef Stolten [a,b]

[a] Forschungszentrum Jülich GmbH, Institute of Energy and Climate Research – Jülich Systems Analysis, 52425 Jülich, Germany
[b] RWTH Aachen University, Chair for Fuel Cells, Faculty of Mechanical Engineering, 52062 Aachen, Germany
[c] Politecnico di Milano, Dipartimento di Energia, Via La Masa, 34, 20156 Milan, Italy

A R T I C L E  I N F O

*Keywords:*
Temporal resolution
Time series aggregation
Renewable energy systems
Self-sufficiency
Lost load
Sub-hourly

A B S T R A C T

Future energy systems incorporating high shares of intermittent renewable energy sources are often designed using optimization-based, bottom-up energy system models. However, such models are generally limited to single years and hourly resolutions. This study quantifies the precision loss between hourly and sub-hourly-resolved data for the design and operation of a self-sufficient residential multi-energy system with respect to total costs, system design, and reliability using both averaging and sampling data methods. In this case study, the total annual cost is underestimated by 1.7% with the average hourly data relative to the fully-resolved minute resolution data, mainly due to the sizing of the photovoltaic inverter and battery. This is a result of the sub-hourly peaks in the supply and demand data that are evened out, significantly impacting the sub-electrical system. The results show up to 89 kWh of the annual lost load of the total electrical and thermal load, and a penalty cost of up to €894 (+24%) based on the value of the lost load. Another method, which employs regular sampling of the original time series, shows unpredictable behavior with respect to the tendency of either over- or underestimating system costs and components' capacities depending on the selected samples. Both the sampling and averaging methods highlight that while hourly resolution may suffice for total system cost approximations, it falls short of sizing dynamically-operated components and meeting stringent reliability requirements. Future research may aim to enhance the temporal resolution of global intermittent renewable energy sources and reduce the computational expenses associated with minute-level resolutions.

## 1. Introduction

The energy sector has recently been characterized by a remarkable surge in renewable energy sources as the cornerstone for future sustainable energy systems [1]. Some of these renewable energy sources are non-dispatchable, as they exhibit intermittent power production such as the diurnal cycle of photovoltaic availability during the day and its unavailability at night. Energy system modeling has emerged as a technique to enable a better understanding of the energy system to be gleaned and to guide its successful transition. It includes a suite of mathematical and computational tools to simulate, analyze, and optimize the energy system's operation and aids in understanding the complex interplays between various components in generation, transmission, distribution, and storage [2]. This allows for informed decisions to be made about the energy system design, operational strategies, and resource allocation.

Energy system models were developed during the latter part of the twentieth century [3,4] and assist in evaluating the economic feasibility of different energy technologies and their integration into the existing system [5]. They play a crucial role in assessing the environmental sustainability of energy systems by quantifying greenhouse gas emissions, air pollution, and other environmental externalities [6]. By taking into account the inputs from diverse sources and experts, these models can provide a holistic view of the energy system, taking into account technological advancements, policy frameworks, economic factors, and environmental considerations [7].

A growing number of studies model different energy scenarios, especially using bottom-up energy system optimization to economically and sustainably meet energy demand. Some of these include capacity expansion, economic dispatch, and the power market. However, the accuracy and reliability of the modeled system designs depend

* Corresponding author at: Forschungszentrum Jülich GmbH, Institute of Energy and Climate Research – Jülich Systems Analysis, 52425 Jülich, Germany.
*E-mail address:* o.omoyele@fz-juelich.de (O. Omoyele).

https://doi.org/10.1016/j.enbuild.2024.114411
Received 15 March 2024; Received in revised form 20 May 2024; Accepted 8 June 2024
Available online 22 June 2024

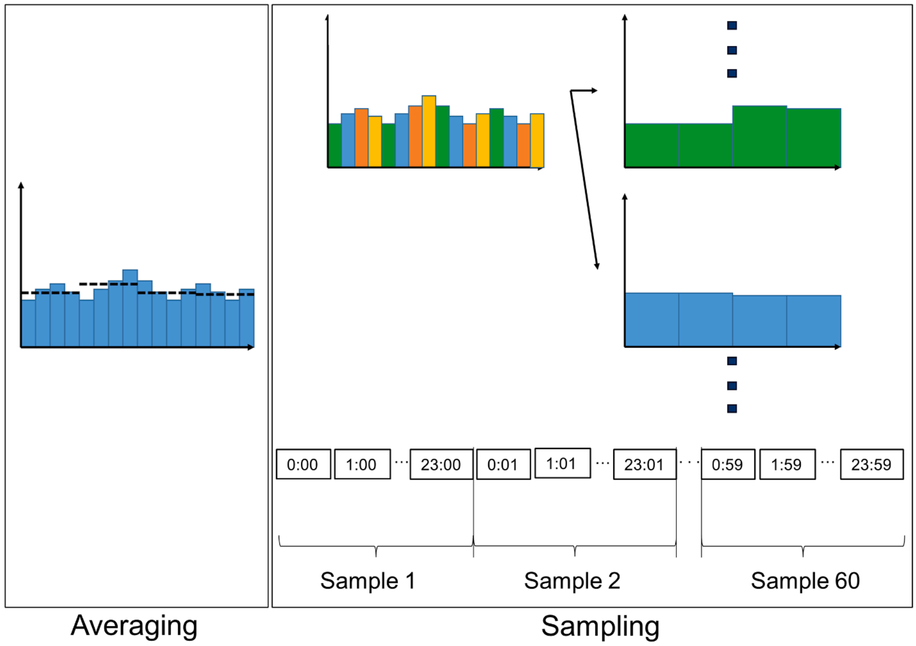



**Fig. 1.** The down-sampling approaches employed: left: using averaging; right: using equidistant sampling.

profoundly on the temporal resolution applied in the models [8]. The temporal resolution refers to the intervals at which data is recorded. The choice of temporal resolutions affects many system aspects, such as cost accuracy, computational complexity, operation, and component sizing of energy system models [8]. The choice of an appropriate temporal resolution is not only pivotal for achieving the optimal design of energy system models but also for addressing contemporary challenges such as the reliable integration of intermittent renewable energy sources, the dynamics of energy markets, and the pressing need for sustainability [9].

Most models determine optimal energy systems using an hourly resolution [2,8,10]. This is due to the resulting lower model complexity and higher data availability for hourly models as present in several databases such as renewable.ninja [11,12], EMHIRES [13], Open Power System Data [14], ERA5 Reanalysis [15], MERRA2 Reanalysis [16], C3S [17], NREL NSRDB [18], PECD for ENTSO-E [19], as compared to sub-hourly resolution. Meanwhile, sub-hourly data is closer to real-time than the hourly resolution, as the output of intermittent renewable energy sources can change significantly within an hour.

Even though hourly modeling is more popular and less complex, the significant impact of sub-hourly variance on different energy systems has been investigated in some studies. When minute-based data is available, the high-resolution data is frequently down-sampled to lower resolution by either averaging or sampling to address computational complexity. Averaging refers to taking the mean at specific periods, whereas sampling is taking one instantaneous data point from the original dataset at specific periods, as is shown in Fig. 1. Table 1, presenting the most recent literature, shows that hourly modeling can either under- or overestimate energy system modeling results (as seen in the parameters and conclusions columns), depending on the considered parameters or down-sampling methods used. Although some studies reported a significant underestimation by hourly resolution compared to the minute-level in the annual generation or operating costs of systems through the averaging method, to the best of the authors' knowledge, an assessment of the actual reliability and feasibility of the systems derived from hourly data is lacking. In addition, down-sampling via the sampling method by only considering the instantaneous values of single time points at every hour is biased, as the data points are bootstrapped to represent the full hour.

The present study amends these limitations by quantifying the impact of sub-hourly resolution at 60-, 30-, 15-, 10-, 5-, and 1-minute intervals using both the average and sampling methods for self-sufficient buildings. In 2022, residential and industrial buildings accounted for 9.9% and 28.9% of global carbon emissions, respectively [20]. The purpose of self-sufficient buildings is to supply energy on-site, drawing on renewable resources such as wind and solar power [21]. The objective is to minimize dependency on conventional power systems, cutting carbon emissions, and potentially reducing energy costs. Furthermore, decentralized and even 100% renewable energy systems are a constantly evaluated topic in the literature [9]. This is because they are not only an option for defossilization but also likely increase energy accessibility in remote, geographically-isolated or underdeveloped rural areas, and even for increasing access to energy in general [22]. Therefore, with rising electricity procurement costs and decreasing costs for renewables and storage, many households could strive for energy self-sufficiency in the future [23]. The solution of a minute-based energy system model is computationally extremely demanding. For that reason, a self-sufficient building model is an application case with an appropriate size, on the one hand, and no external assumptions to be made on parameters like prices on the other. As reliability is the most challenging case for self-sufficiency, we follow a conservative approach to quantify the impact of sub-hourly profiles. With the implementation of a self-sufficient building model, buildings can reduce their carbon footprint and gain control over their costs and energy consumption. This will help in the building of a more resilient and sustainable future. The remainder of this paper is as follows: Section 2 deals with data collection, and the energy system modeling case study of self-sufficient building. Subsequently, Section 3 discusses the results of the case study in terms of the total annual costs and the installed capacities of the components. Furthermore, the impact of the lost load is quantified in this section. Finally, Section 4 presents the conclusions of this study.

## 2. Methods

This section presents the supply and demand time series data considered as well as the downscaling approaches in averaging and sampling employed (Section 2.1). Additionally, Section 2.2 considers the case study and the associated capacity expansion equation, whereas the sensitivity and reliability analyses are presented in Section 2.3.

### 2.1. Time series data and down-sampling approaches

The high-resolution global horizontal irradiance (GHI) is obtained as

**Table 1**
Review of the impacts of temporal resolution on energy system modeling. The table shows various articles that compare different energy system modeling, the model type, and technologies (which represent the type of energy system considered), temporal resolutions, down-sampling methods, parameters of consideration and conclusions that show the effect of the lowest relative to the highest resolutions considered within the parameters. For example, in Ernst and Gooday [29], the inverter clipping losses is underestimated, whereas the performance ratio is overestimated. The abbreviated words in the table are Economic Dispatch (ED), Unit Commitment (UC), Photovoltaic (PV), Concentrated Solar Power (CSP), and Levelized Cost of Electricity (LCOE).

| Authors | Technology | Model type | Temporal resolutions | Down-sampling methods | | Parameters | Conclusions |
|---|---|---|---|---|---|---|---|
| | | | | Average | Sample | | |
| Gangammanavar et al. [24] | IEEE-RTS96 system/ Illinois system | ED | 1 h, 30, 20, 10 min | ☑ | ☑ | Operational cost | Underestimated |
| Troy et al. [25] | Irish 2020 system | UC&ED | 1 h to 15 min | ☑ | ☒ | 1. Generator cycling<br>2. Flexible generation<br>3. Storage utilization | 1. Underestimated<br>2. Underestimated<br>3. Underestimated |
| O'Dwyer et al. [26] | Plant portfolio for Ireland in 2025 | UC&ED | 1 h to 15 min | ☑ | ☒ | 1. Storage plant cycling<br>2. Energy storage | 1. Underestimated<br>2. Underestimated |
| Lopez et al. [27] | All-Island of Ireland system/ DE/AT power systems | UC&ED | 1 h to 15 min | ☒ | ☑ | Ramping | Underestimated (up to 4.5 higher) |
| Meybodi et al. [28] | parabolic trough plants | UC&ED | 1 h, 30, 15, 5 min | ☑ | ☒ | A more realistic view of short-term operation that can be used for optimizing the control system | |
| Ernst and Gooday [29] | PV plant | Simulation | 1 h, 30, 15, 10, 5, 1 min | ☑ | ☒ | 1. Inverter clipping losses<br>2. Performance ratio | 1. Underestimated (0.4% to 2.2%)<br>2. Overestimated (1.1%) |
| Martin Janos Mayer [30] | Ground-mounted photovoltaic plants | Techno-economic optimization | 1 h, 30, 15, 10, 5, 1 min | ☑ | ☑ | 1. LCOE<br>2. Inverter sizing ratio | 1. Underestimated (3%)<br>2. Overestimated |
| Deane et al. [31] | Irish power system | UC&ED | 1 h, 30, 15, 5 min | ☑ | ☒ | Generation cost | Underestimated (1%) |
| Kazemi et al. [32] | IEEE 118-bus test system | UC&ED | 1 h, 30, 15, 10, 5 min | ☑ | ☒ | 1. Production costs<br>2. Reserves | 1. Underestimated<br>2. Underestimated |
| Zurita et al. [33] | Hybrid CSP-PV plant | Simulation | 1 h, 30, 15, 10, 5, 1 min | ☑ | ☒ | 1. Total yearly production of the hybrid plant<br>2. LCOE | 1. Overestimated<br>2. Underestimated |
| Bistline [34] | Electric sector | Capacity planning and ED | | ☑ | ☒ | Policy analysis, electric sector planning, and technology valuation | Higher temporal resolution is increasingly important |
| Kërçi et al. [35] | IEEE 39-bus | UC | 15, 5 min | ☑ | ☒ | Frequency fluctuations | Higher temporal resolution leads to lower frequency fluctuations |
| Hofmann and Seckmeyer [36] | PV system simulation | Simulation | 1 h, 1 min | ☑ | ☒ | Inverter clipping losses | Underestimated |
| Villoz et al. [37] | PV system | Simulation | 1 h, 1 min | ☑ | ☑ | Inverter clipping losses | Underestimated (up to 5%) |
| Hrvoje Pandžić [10] | 24-bus IEEE-RTS | UC | 1 h, 15 min | ☒ | ☑ | Operating cost | Overestimated |
| Klokov and Loktionov [38] | Off-grid systems, Alps | Optimization | 5, 10, 15, 20, 30 min, 1, 2, 3, 4 h | ☑ | ☒ | 1. Energy storage charge–discharge cycles<br>2. Equipment cost<br>3. Longest Duration of Operation Interruption | 1. Underestimated<br>2. Underestimated<br>3. Overestimated |

minute-measured data [42]. For further analyses, the irradiance is averaged over 5, 10, 15, 30, and 60 min or sampled every hour, as is shown in Fig. 1. As the 60-minute data is ubiquitous and therefore used by many researchers, the use of sampled irradiance data is only explored for the 60-minute interval. The various hourly samples (60 samples every hour) in the minute-based irradiance are holistically explored to quantify how these affect the robustness of the energy system and obtain the average result of these samples. Fig. 2 shows the yearly profile of the solar irradiance, which is further analyzed to yearly duration curves for the averaged and sampled irradiance, as shown in Fig. 3 and Fig. 4, respectively. The irradiance at different resolutions is converted into the capacity factor time series for energy system modeling using the direct current photovoltaic output method of Riffonneau et al. [43].

The high resolution data capture spikes which are evened out in the lower resolution for averaged irradiance, Fig. 3 and potentially get retained for sampled irradiance, Fig. 4. Fig. 4 also shows an inconsistent result for the sampling method (Sample 1 is considered), in which the coarser profiles can either be above or below the one-minute resolution profile. The duration curve for the sampled data depends on the order of the sample. A day line plot for the average and sampled irradiance, revealing how the peak irradiance values are affected at hourly and sub-hourly resolutions are shown in Appendix A.1. Appendix A.2 also outlines the statistical distribution of the average and sample upscaling approaches involving the mean, median, minimum, maximum, first quartile, and third quartile values.

The demand data (simulated) for a single-family household with two working parents and three children (travel route set for 5 km community distance, bus and one 30 km/hr car, charging at home with 22 kW) was obtained using the LoadProfileGenerator by Pflugradt and Muntwyler [44,45] and the Household Infrastructure and Building Simulator (HiSim) for the analysis and simulation of building systems.[1] The LoadProfile-Generator model is a behavioral framework based on desires and user-defined activities called 'affordances'. The one-minute data from the

[1] https://github.com/FZJ-IEK3-VSA/HiSim.

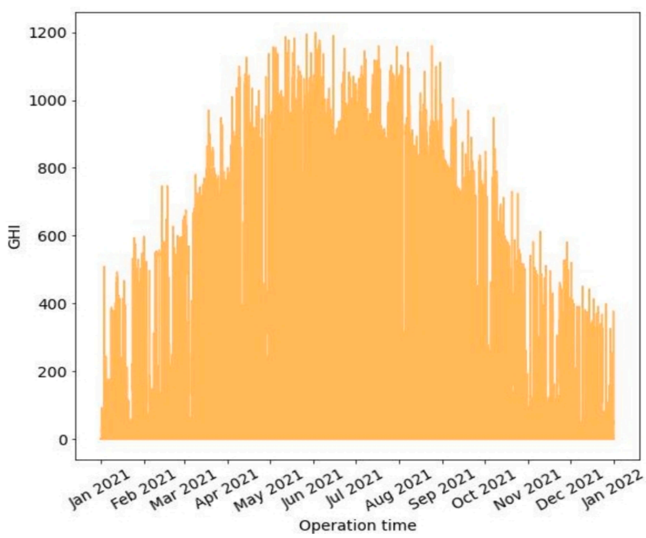



**Fig. 2.** Plot of the global horizontal irradiance (GHI) for the year 2021 at the location in Milan, Italy (lat.: 45.5028249, long.: 9.1561092).

LoadProfileGenerator and HiSim is also averaged and sampled as in the case of the global horizontal irradiance data above.

### 2.2. Case study

To investigate the impact of different temporal resolutions on energy system modeling, a self-sufficient building is considered. The self-sufficient building model employed in this study, as depicted in Fig. 5, was originally developed by Kotzur et al. [46], and further expanded by Knosala et al. [39] and Hoffmann et al. [47,48], who sought to minimize the total annual system costs. This model aims to integrate renewable energy (photovoltaics), efficient energy storage systems (battery, thermal, hydrogen, and liquid organic hydrogen carriers), and advanced energy management strategies to achieve the optimal utilization of resources and reduce reliance on energy providers. The self-sufficient building model considered in this study is modeled using the ETHOS. FINE framework [40,41], the underlying equations for which are provided in Eqs. (1)–(10). Appendix A.3 provides an overview of the capital, and operational expenditures (fixed and capacity-specific) and lifetimes of the technologies as developed by Knosala et al. [39].

In the following, we present the most important equations relating to the capacity expansion optimization of the self-sufficient building. In these, $M^y$ represents the subsets of the components, at which y can be sources, sinks, converters (conv), storage (store), and commodities (g). T is the amount of required time steps, $x^{op}$ is the operation rate variable, which extends to charge (ch) and discharge (dis) as in storage, $x^{SOC}$ represents the state of charge variable, $x^{cap}$ is the installed capacity variable, and f is the commodity flow variable.

The objective function Eq. (1) is to minimize the total annual cost of the system comprising the capital (CAPEX) and operational (op) expenditures of the components.

$$min\left(\sum_{c}\left(C_{c}^{capex}+\sum_{t}C_{c,t}^{op}x_{c,t}^{op}\right)\right) \qquad \forall c \in M,\ t \in T \tag{1}$$

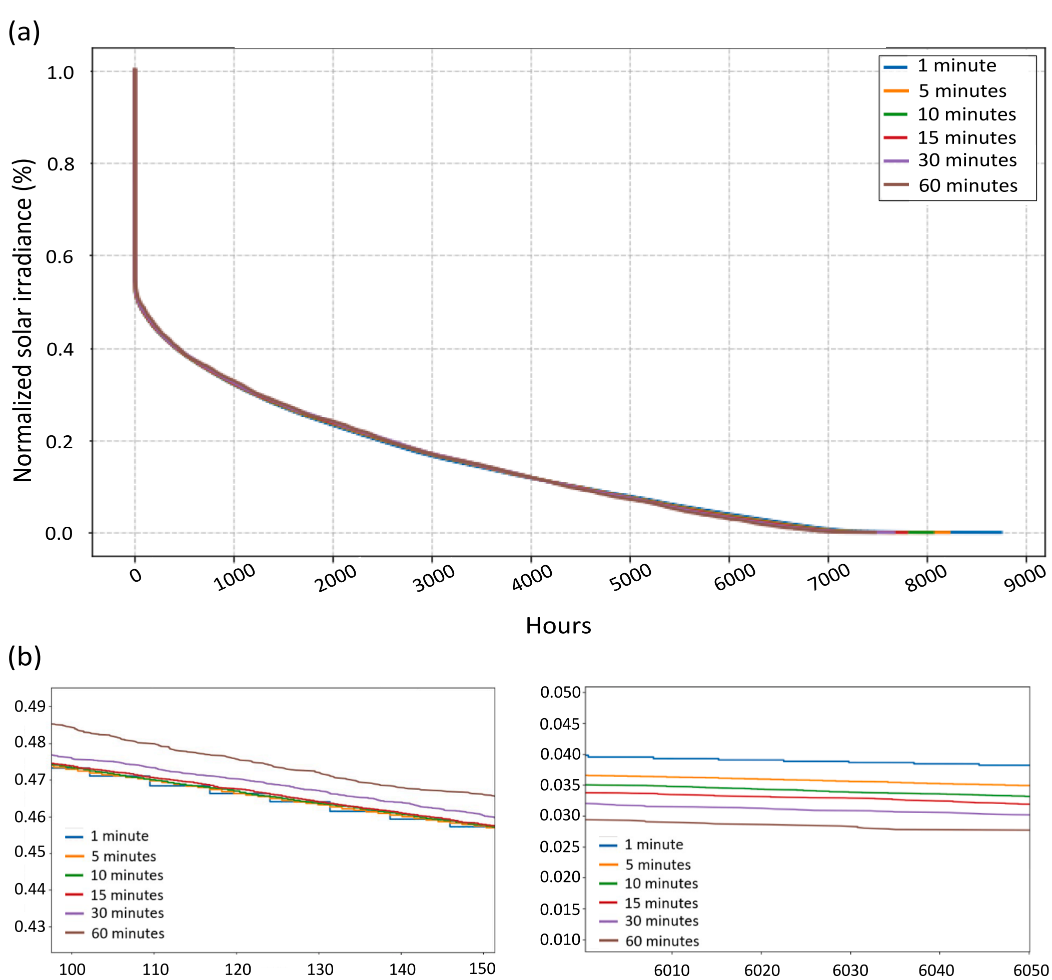



**Fig. 3.** (a) Yearly duration curve of the one-minute irradiance data averaged to 5, 10, 15, 30, and 60 min; (b) zoomed average duration curve.

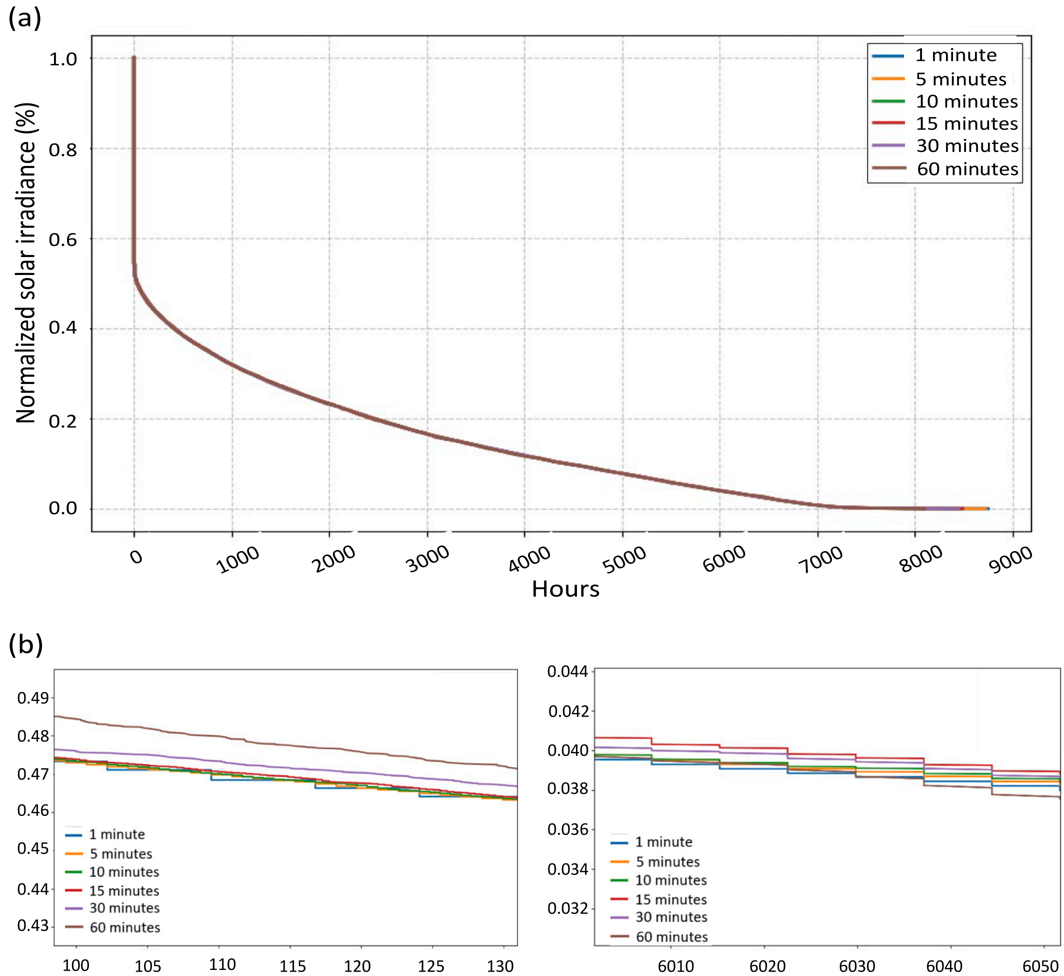



**Fig. 4.** (a) Yearly duration curve for the one-minute irradiance data sampled to 5, 10, 15, 30, and 60 min; (b) the zoomed sample duration curve.

Eq. (2) ensures a net balance of the commodities (electricity, heat, and hydrogen).

$$\sum f_{c,t} = 0 \qquad \forall\ c \in M^g,\ t \in T \tag{2}$$

Eqs. (3)–(5) ensure a commodity flow for the source, sink, and converters, respectively. $\gamma$ is the conversion factor from one commodity to another.

$$f_{c,t} = x_{c,t}^{op} \qquad \forall\ c \in M^{source}\ \cap\ M^g,\ t \in T \tag{3}$$

$$f_{c,t} = -x_{c,t}^{op} \qquad \forall\ c \in M^{sink}\ \cap\ M^g,\ t \in T \tag{4}$$

$$f_{c,t} = \gamma_{c,t} x_{c,t}^{op} \qquad \forall\ c \in M^{conv}\ \cap\ M^g,\ t \in T \tag{5}$$

Eq. (6) represents the storage flow. The operational bounds for the component are represented by Eqs. (7) and (8).

$$f_{c,t} = x_{c,t}^{op,dis} - x_{c,t}^{op,ch} \qquad \forall\ c \in M^{store}\ \cap\ M^g,\ t \in T \tag{6}$$

$$x_{c,t}^{op} \geq 0 \qquad \forall\ c \in M^{source,sink,conv,store},\ t \in T \tag{7}$$

$$x_{c,t}^{op} \leq x_c^{cap} \qquad \forall\ c \in M^{source,sink,conv},\ t \in T \tag{8}$$

The state of charge of the storage between the present and previous time steps is represented by Eq. (9), whereas Eq. (10) defines the lower and upper bounds of the state of charge. η represents the efficiency.

$$x_{c,t+1}^{SOC} = x_{c,t}^{SOC} + \eta_{c,t}^{ch} x_{c,t}^{op,ch} - \frac{x_{c,t}^{op,dis}}{\eta_{c,t}^{dis}} \qquad \forall\ c \in M^{store},\ t \in T \tag{9}$$

$$0 \leq x_{c,t}^{SOC} \leq x_c^{cap} \qquad \forall\ c \in M^{store},\ t \in T \tag{10}$$

The optimization models were computed on a high-performance computing cluster using the technical specifications listed in Table 2. Each optimization was run with the same specification to allow for an unbiased assessment of the impact of temporal resolution on computational run time.

### 2.3. Sensitivity analysis and reliability assessment

In the first step, the self-sufficient building model described in Section 2.2 was solved using the minute-resolved time series data specified in Section 2.1. Then, we used averaging to resolve the model for progressively lower temporal resolutions (5, 10, 15, 30, and 60 min) to quantify the impact on the device capacities and the total annual system cost. Note that the hourly resolution is the status quo in most of the current energy system studies.

In the second step, we quantified the impact of using hourly data on the resulting system layout's supply reliability. For that, a lost load analysis was conducted using hourly data for the design optimization and minute-level data for a validation of the operational feasibility. The Value of Lost Load (VoLL) is the quantitative measure of electricity customers' willingness to pay for the security of supply [49].

Fig. 6 demonstrates the procedure to quantify the amount of lost load and its value. For the process, the capacities obtained from the optimization results with the hourly data are maximally fixed. Then, another optimization was run with the fixed capacities using the one-minute data. To ensure the feasibility of the second dispatch-only

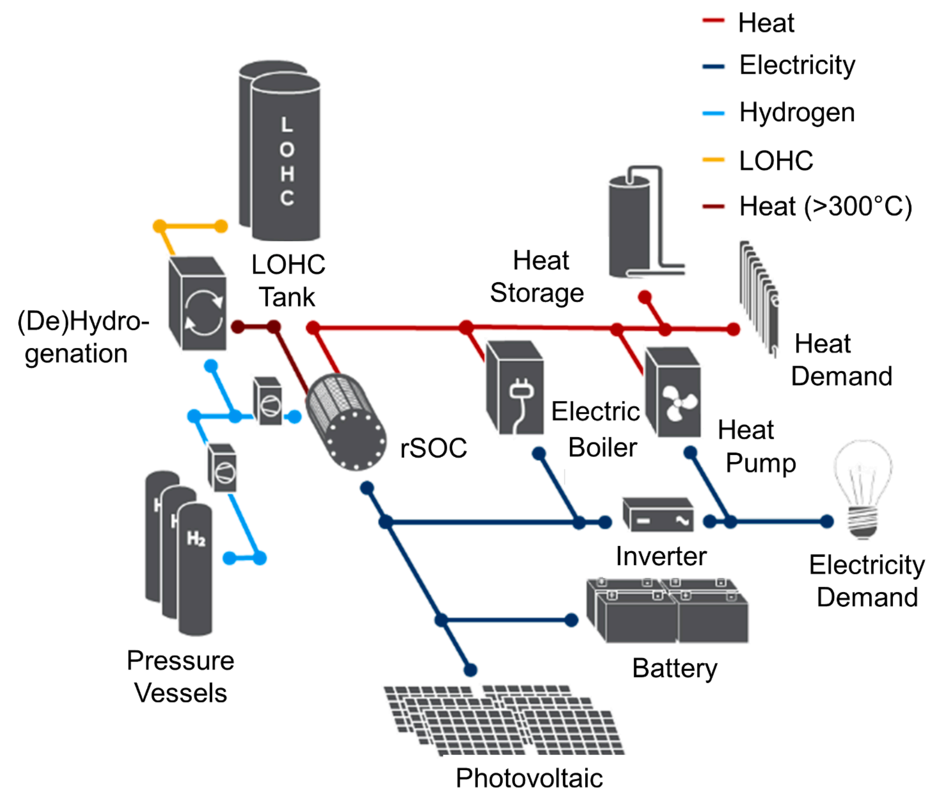



**Fig. 5.** Scheme of the self-sufficient building model as presented by Knosala et al. [39]. The LOHC and rSOC represent liquid organic hydrogen carriers and reversible solid oxide cell respectively.

**Table 2**
Computational resources used for the optimization runs.

| Parameter | Specifications |
|---|---|
| CPU-per-task (cores) | 8 |
| Nodes | 1 |
| Memory-per-CPU (GB) | 32,000 |
| Threads | 32 |
| Read access memory (GB) | 256 |

optimization, an auxiliary electricity source was added to the system, which provides power during the outage hours (only theoretically), i.e., at times when the design based on hourly data would be infeasible for the minute-resolved data. Throughout this process, it can be checked if the optimization results from the hourly data provide a feasible design for the minute-level data, i.e., real-world conditions. In reality, the auxiliary source would not exist, in that the electricity provided by the auxiliary source would equal the unmet demand (i.e., the lost load) in the real model. These unmet demands can then be mitigated by implementing demand-side management strategies like peak shavings and real-time pricing. Smart metering technology can also play a crucial role by offering detailed consumption data, enabling consumers to adjust their usage during the peak periods.

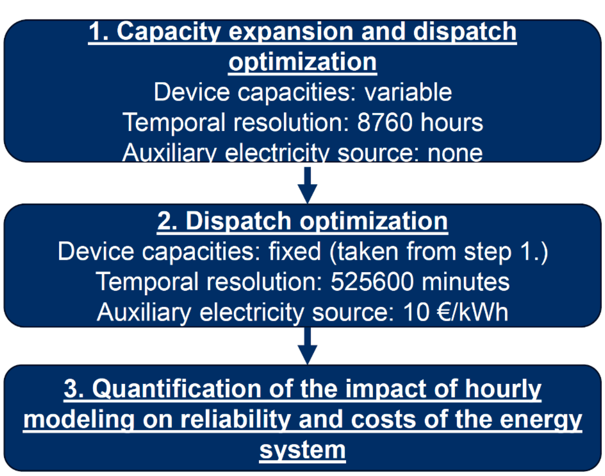



**Fig. 6.** Process of sequential optimizations with variable and fixed capacities for quantifying the lost loads of different system designs.

The estimation of the VoLL in a residential context is based on utilizing a macroeconomics approach and often lies between €10 and €25/kWh, whereas the maximum VoLL in terms of consumer willingness to pay surveys is typically around €10/kWh, as presented by Schröder and Kuckshinrichs [50] and Gorman [49]. Therefore, a VoLL of €10/kWh is assigned as the electricity price provided by the auxiliary source. Note that this price is much higher than the system's levelized cost of electricity, and so the auxiliary source only provides electricity at times when the system would otherwise be infeasible.

Following the reliability test through the VoLL, we assess the question of whether more reliable system designs can be derived by means of equidistant sampling instead of averaging in Section 3.3.

## 3. Results and discussion

This section describes the layout for varying the temporal resolution of the averaging method in Section 3.1, as well as the impact of lost load (Section 3.2) to access the reliability of the hourly resolution. In Section 3.3, the results of the different samples are described, whereas Section 3.4 presents a discussion of the analyses.

**Table 3**
Results for the self-sufficient building model comprising the total annual cost (TAC), capacities for photovoltaic (PV), the inverter and all considered storage types (battery, liquid organic hydrogen carriers, hydrogen, thermal), as well as the computational time using averaging.

| Time step length (min) | TAC (€) | Inverter ($kW_{el}$) | PV ($kW_{el}$) | Battery ($kW_{el}$) | LOHC Storage ($kW_{H2}$) | H2 Storage ($kW_{H2}$) | Thermal Storage ($kW_{heat}$) | Computing time (min) |
|---|---|---|---|---|---|---|---|---|
| 60 | 3677.28 | 5.114 | 14.895 | 7.277 | 5526.98 | 34.049 | 6.983 | 4.78 |
| 30 | 3695.93 | 6.592 | 14.992 | 7.340 | 5518.75 | 34.544 | 7.151 | 19.61 |
| 15 | 3709.54 | 7.628 | 14.950 | 7.591 | 5529.71 | 34.440 | 7.021 | 64.37 |
| 10 | 3716.9 | 8.282 | 14.983 | 7.556 | 5528.44 | 34.569 | 7.034 | 227.80 |
| 5 | 3723.45 | 8.864 | 14.972 | 7.628 | 5533.23 | 34.606 | 6.988 | 666.10 |
| 1 | 3740.11 | 10.673 | 14.971 | 7.702 | 5539.21 | 34.659 | 6.837 | 2354.07 |

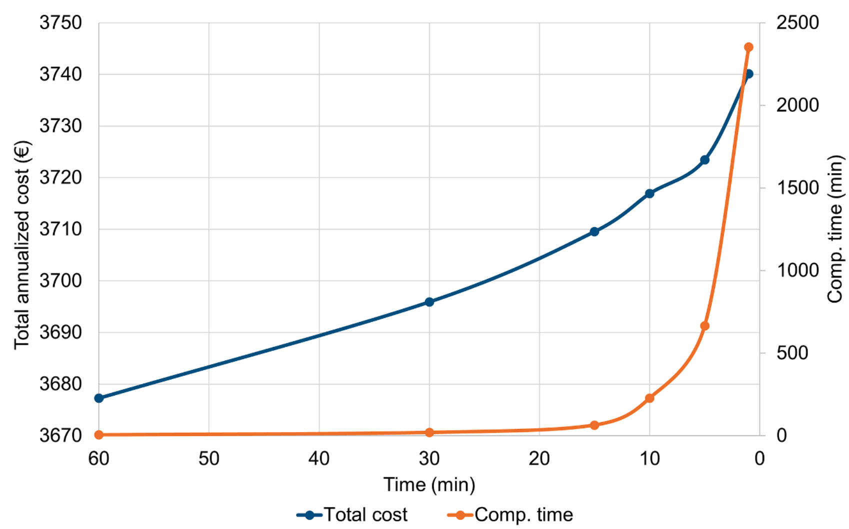



**Fig. 7.** The total cost and computational time of different temporal resolutions.

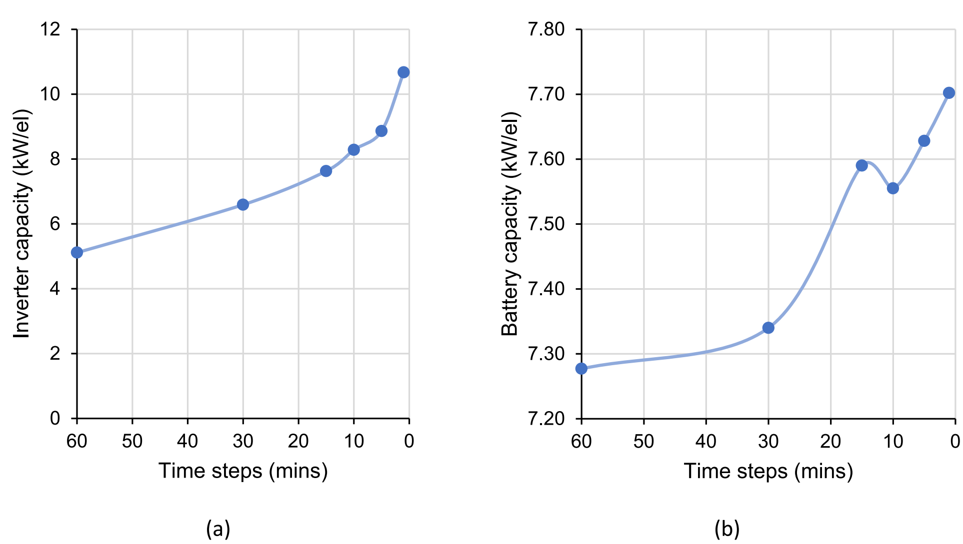



**Fig. 8.** The inverter (a) and battery (b) capacities for different temporal resolutions.

### 3.1. Layouts for varying temporal resolutions (Averaging)

First, we compare the results of the self-sufficient building model using the input data at one, then averaged over 5-, 10-, 15-, 30-, and 60-minute resolutions to examine the impact of sub-hourly resolutions on total annual cost, installed capacities, and computational runtimes. The results are summarized in Table 3.

Table 3 shows some significant variations in the results obtained using the average hourly resolution, sub-hourly averaged, and fully resolved minute-resolution data. The total annual cost of the building increases from €3677.3 to €3740.1 between the hourly and minute-resolved data, leading to a cost underestimation of 1.7% for hourly resolution. However, a major drawback of the sub-hourly resolution other than the dearth of sub-hourly data is the computational complexity (see Fig. 7). The computational runtime increases exponentially with the temporal resolution considered. Furthermore, the

**Table 4**
Results of the lost load analysis.

| Parameter | Value |
|---|---|
| VoLL (€/kWh) | 10.0 |
| Amount of lost load (kWh) | 89.4 |
| Percentage of cost inc. (%) | 24.3 |

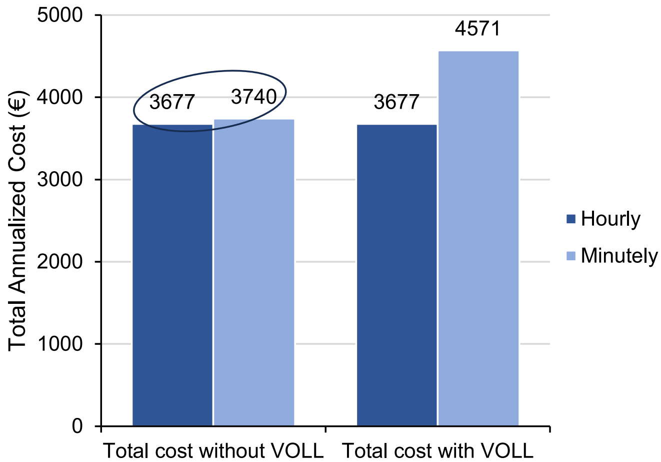



**Fig. 9.** Difference between the total annual costs in optimizations with hourly- and minute-resolved data, as well as with and without considering the VoLL).

inverter and battery sizes both increased with higher temporal resolutions (see Fig. 8). The battery size increased from hourly to minutes from 7.277 $kW_{el}$ to 7.702 $kW_{el}$ (+6%). Even more so, the inverter size doubles when using minute-based data, which is due to the omission of intra-hourly extreme values in the demand and supply data when using hourly-averaged profiles. The inverter is most severely affected by this effect because it is a bottleneck between the supply side with the photovoltaic panels and the demand side with heat and electricity demands.

### 3.2. Value of lost load

The exponential growth of computational complexity as shown in Fig. 7, as well as a lack of data availability, leads to the fact that sub-hourly optimization is still an exception in capacity expansion planning. However, as will be shown in the following, the ubiquitous hourly data is not sufficient for accurate energy system modeling in the case of a self-sufficient system. To quantify the impact on system reliability, the optimization results with hourly data are fixed assuming a setup with the results obtained through this. Then, a highly resolved profile in one minute is fed as input data into the system, rendering the system optimization infeasible. This owes significantly to the inverter and storage sizes that are underestimated as analyzed in the preceding section. For security of supply, a theoretical auxiliary electricity supply is added to the system, whose supply is associated with a penalty cost in the form of the VoLL. Table 4 shows the results obtained from the analysis.

Although an underestimation of 1.7% in total annual costs occurs between the hourly and minute-based optimization run, it is not advisable to model off-grid systems using hourly resolutions (see Fig. 9). Beyond the 1.7% cost increase, it does not guarantee a reliable power supply, as there is 89.4 kWh of unserved demand, which will lead to hours of annual power outages. If the VoLL of €10/kWh is taken into account, the total annual cost for the energy supply would increase by 24%. While electricity can be purchased from the grid to buffer for the hours of lost load in several systems that are not self-sufficient (i.e., with grid connections), a self-sufficient building should be modeled at a much higher resolution, or account for the cost-underestimating tendency of hourly-resolved data by means of safety factors.

### 3.3. Under- and overestimation of component sizes

The averaging of the input parameters evens out the extreme values, which triggers an underestimation of equipment capacity, most severely affecting those components with highly dynamic operational behavior, such as inverter and battery. These dynamic components act as a bridge between the supply and the demand sides of the energy system. As is shown in Table 1, some researchers opted for sampling equidistant values from the original dataset instead of averaging. The results for the components that changed significantly along with the impact on total annual costs are shown in Fig. 10. The sampled data is distributed as single points to show that it can either underestimate or overestimate the cost and installed capacities of the system, depending on the starting point of the sample. Concretely, when sampling hourly values from minute-based data, one can either use the value of every first, second, third, and up to sixtieth minute of each hour, yielding 60 different samples in total (as is shown in Fig. 1).

The average of all 60 model runs with sampling provides an overestimate with respect to the total system costs. Furthermore, it can be observed that the sampling generally underestimates the inverter size, but by far not as severely as the averaging method. Overall, at least the average design obtained with sampling is deemed more reliable to model energy systems at the minute resolution level than averaging the input data.

The averaging method, even though not reliable, is associated with a lower computational runtime and underestimates the results. The sampling method either underestimates or overestimates the system's cost and installed capacities with energy reliability (depending on the sampling points), but is also much less complex than the fully-resolved minute resolutions. Sampling plus averaging (at which the average of the sampled results is taken) mostly provides a more reliable result and similar computational complexity as averaging.

### 3.4. Discussion

A plethora of literature has discussed the importance of sub-hourly resolutions in energy system modeling and the deficiency in the hourly models as shown in Table 1. However, many studies consider large systems from district to national, and to the best of the authors' knowledge, an assessment of the impact on self-sufficient residential buildings is missing. Energy self-sufficient buildings are constantly gaining momentum with rising electricity costs and the decrease in the costs of renewables and storage [23]. As a result of this, self-sufficient buildings could then become part of the defossilization process, as many houses might strive for self-sufficiency in the future [23]. Nonetheless, the common hourly resolution modeling may not be sufficient for such a conservative energy system as that shown in Table 3, with data averaging also commonly used. While an underestimation of 1% was concluded in the generation cost of the Irish power system by Deane et al. [31] between 1-hour and 5-minute resolutions, our studies found a similar result and even an underestimation of 1.7% between the hourly and minute resolutions for the total annual cost. It can be inferred from Table 3 and Fig. 7 that a cost underestimation and computational rise from €3677 to €3723 (1.2%) and 4.8 to 666.1 min (a factor of 140), respectively, occurred between the hourly and 5-minute resolutions. Similarly, a cost underestimation and computational rise from €3677 to €3740 (1.7%) and 4.8 to 2354.1 min (a factor of 493), respectively, occurred between the hourly and 1-minute resolutions. A compromise of 5-minute-resolution modeling can be concluded between the accuracy and computational complexities. Moreover, the total annual cost underestimation only illuminates a limited facet of the issue, whereas a broader one is associated with reliability, especially in a self-sufficient energy system. With respect to that, the hourly resolution systems suffer a loss of up to 89.4kWh annually (electricity and heat). With the

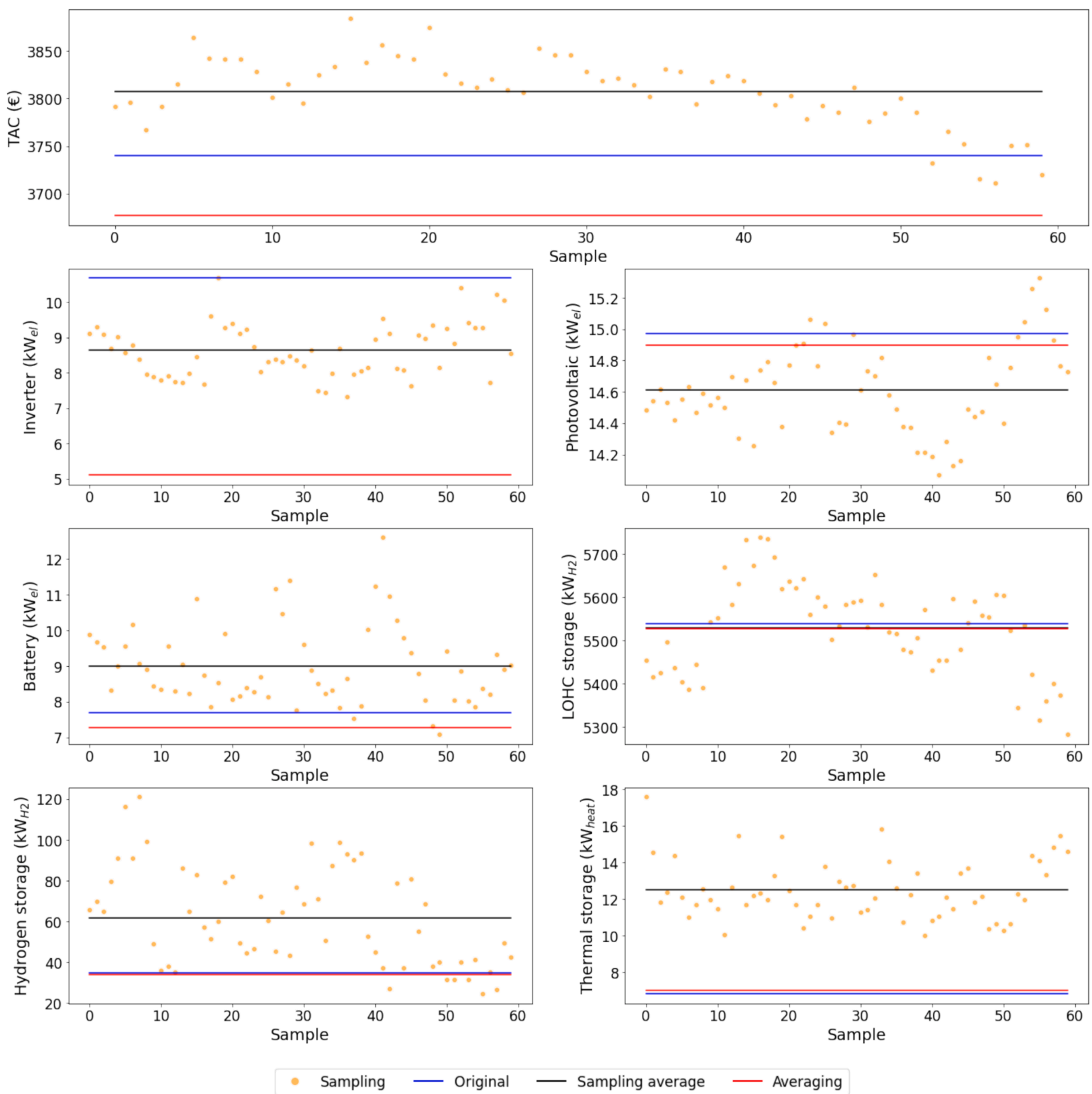



**Fig. 10.** Total annual cost (TAC) and installed capacities (inverter, photovoltaic, battery, liquid organic hydrogen carriers (LOHC) storage, hydrogen storage, and thermal storage) for the sampled data (sampling), original or fully-resolved minute data (original), an average of the sampled results (sampling average), and the averaged data (averaging).

VoLL of 10 €/kWh, this raises the actual cost underestimation between the hourly and minute resolutions to 24.3% (Table 4 and Fig. 9). Additionally, the non-reliability that arises from the non-feasibility of the system arises from the underestimated system capacity (Table 3 and Fig. 8). The inverter, which is the bridge between the demand and supply from the photovoltaic panels, as well as the battery shows underestimations because the peak power from the irradiation and peak demands have been averaged out in the hourly resolution, thereby not capturing the intra-hour variations. Thus, during peak demand periods, the systems' capacities are not sufficient to buffer such arbitrage. These underestimated capacities reduce the associated costs for the components, thereby underestimating the total annualized cost.

As averaging minimizes the maxima, this leads to an underestimation. Studies are then carried out on hourly point sampling with one-minute resolutions as a reference, as is shown in Fig. 1. It can be inferred that sampling 60 points between hours provides either an underestimation or overestimation of the system's costs and capacities depending on the sampling points, as depicted in Fig. 10. As the sampling points that accurately give the solution cannot be deciphered in advance, the average of the solutions from the samples is taken (Fig. 10), as assumed by Villoz et al. [37] as an alternative to solving complicated minute resolution problems. This indicates an overestimation of the total annualized cost (1.8%) and some of the systems' capacities (Fig. 10), which also does not provide an accurate solution. However, the dynamic components are less biased and the problem is less complicated, as this can solve at approximately the computational runtime of the hourly average resolutions with parallel calculation on the high performance computing cluster.

As is made evident in this study, it is pertinent to model self-sufficient energy systems, that rely on intermittent renewable energy sources, using high-resolution data such as minute by minute data. This helps to both capture accurate cost approximations and dynamic component sizing in the design of future energy systems with high shares of intermittent renewable sources. The relevance of temporal resolution discussed in this work can help increase the accuracy of modeled energy systems, and is also a pivotal tool towards a more sustainable future. Although this study offers useful insights into the modeling of an energy system considering a self-sufficient building, it is limited to a single location in Europe. Future work could therefore focus on modeling multiple locations covering the Köppen–Geiger weather climate and developing models for reducing the computational expenses of minute resolutions. To address the huge computational cost of fully-resolved models, future research could focus on advanced temporal aggregation methods such as K-centroid, K-medoid, and hierarchical clustering to reduce the exponential time while maintaining some substantial levels of accuracy [3,47,48,51–53]. Additionally, future research could also focus on methods to increase the temporal resolution of intermittent renewable energy sources on a global scale.

## 4. Conclusions

In the context of energy system modeling, the right level of detail is a crucial aspect for obtaining computationally-reasonable and sufficiently accurate results. This study reveals the considerable impact of the temporal input data resolution on the cost-optimal system design of a self-sufficient European building in the year 2030. As the temporal resolution varies between 1, 5, 10, 15, 30, and 60 min in this case study, the impact on the system cost and design becomes increasingly evident. Averaged hourly data underestimated the total annual cost by 1.7% compared to minutely-resolved data, whereas the inverter size was underestimated by 50% and the battery capacity by 5.5%. This indicates that especially for domestic electrical sub-systems and reliability assessments, hourly resolutions do not necessarily suffice. Accounting for the amount of lost load with hourly compared to minute-resolved optimization, while assuming €10/kWh as the VoLL, leads to an increase of 24% in the total system costs.

Another method based on regular sampling (i.e., taking every 60th value of the original time series) was used for comparing the hourly- and minute-resolved optimizations. The results with sampling show unpredictable behavior with respect to the tendency of either underestimating or overestimating system costs. Sampling yields better results with respect to the sizing of the inverter, i.e., highly dynamically-operated components are less biased. In energy system modeling, especially in scenarios in which conservative designs are paramount, as in the case of self-sufficient buildings, sole reliance on hourly resolutions may prove inadequate. Hence, there exists a pressing need to transition towards finer-resolution modeling, encompassing sub-hourly intervals, even down to one-minute resolutions. While the importance of temporal resolution is relevant in the context of reliability and rentability, the computational runtime of energy system optimizations between 60 and one minute increased exponentially by a factor of roughly 500. The increased computational runtime is one of the drawbacks of sub-hourly modeling. Nevertheless, a complexity management approach in the form of temporal aggregation could help reduce the complexity while maintaining good accuracy in future research. Another drawback of sub-hourly modeling that could be further improved is the availability of minute-resolved input datasets. If available, our analysis could be replicated in further locations in other countries around the world.

### CRediT authorship contribution statement

**Olalekan Omoyele:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Silvana Matrone:** Writing – review & editing, Conceptualization. **Maximilian Hoffmann:** Writing – review & editing, Visualization, Supervision, Formal analysis, Conceptualization. **Emanuele Ogliari:** Writing – review & editing, Data curation, Conceptualization. **Jann Michael Weinand:** Writing – review & editing, Visualization, Supervision, Formal analysis, Conceptualization. **Sonia Leva:** Writing – review & editing. **Detlef Stolten:** Funding acquisition.

### 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

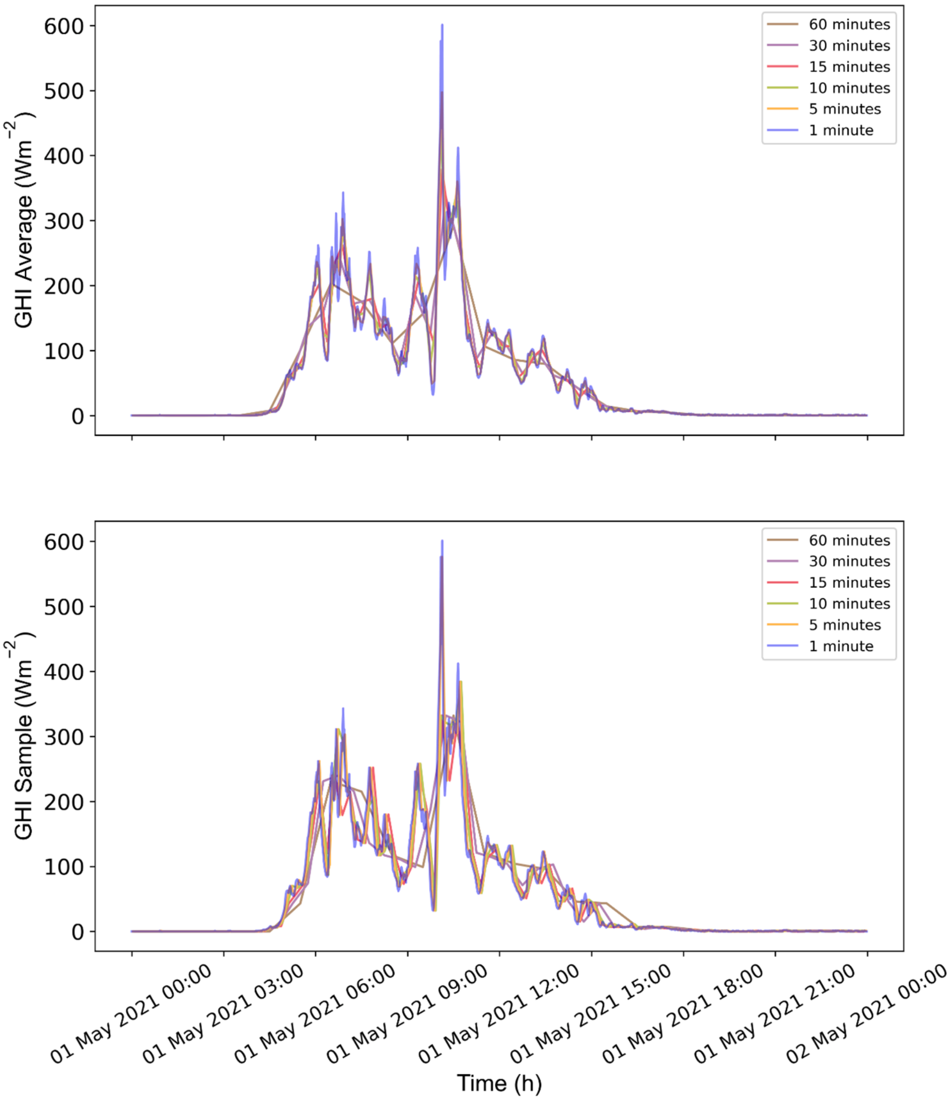
The authors do not have permission to share data.

### Acknowledgement

This work was supported by the Helmholtz Association under the program, “Energy System Design.”

## Appendix A

*A.1. A day line plot of 1, 5, 10, 15, 30, and 60 min with average (top figure) and sampled data (bottom).*




*A.2. Statistical description of the averaging and sampling/up-sampling approaches for the solar irradiance data.*

| | 1 min | Average | | | | | Sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 5 min | 10 min | 15 min | 30 min | 60 min | 5 min | 10 min | 15 min | 30 min | 60 min |
| Mean | 162.71 | 162.71 | 162.71 | 162.71 | 162.71 | 162.71 | 162.64 | 162.69 | 162.75 | 162.6 | 162.7 |
| Min. | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| First quartile | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Median | 4 | 4.4 | 4.6 | 4.73 | 5.1 | 7.15 | 4 | 4 | 4 | 4 | 5 |
| Third quartile | 241 | 245 | 246.83 | 249.4 | 253.38 | 251.28 | 241 | 241 | 242 | 241 | 242.25 |
| Max | 1199 | 1126.8 | 1104.4 | 1068.27 | 1050.33 | 1024.6 | 1195 | 1159 | 1163 | 1157 | 1110 |

### A.3. Cost parameters of the self-sufficient building model according to Knosala et al. [39]

| | Capex | | | Opex | Lifetime (years) |
|---|---|---|---|---|---|
| Components | Fixed (€) | Capacity-specific | | Fixed+capacity-specific (% inv/a) | |
| Photovoltaic ground | — | 4000.00 | €/$kW_p$ | 1.00 | 20 |
| Photovoltaic rooftop | — | 769.00 | €/$kW_p$ | 1.00 | 20 |
| Inverter | — | 75.00 | €/$kW_p$ | — | 20 |
| Battery | — | 301.00 | €/$kWh_p$ | — | 15 |
| Reversible Solid Oxide Cell | 5000.00 | 2400.00 | €/$kW_{el}$ | 1.00 | 15 |
| Heat pump | 4230.00 | 504.90 | €/$kW_{th}$ | 1.50 | 20 |
| Thermal storage | — | 90.00 | €/$kWh_{th}$ | 0.01 | 25 |
| E-Heater & e-boiler | — | 60.00 | €/$kW_{th}$ | 2.00 | 30 |
| Tank | — | 0.79 | €/$kWh_{H2}$ | — | 25 |
| Dibenzyltoluene | — | 1.25 | €/$kWh_{H2}$ | — | 25 |
| Hydrogen vessels | — | 15.00 | €/$kWh_{H2}$ | — | 25 |
| Hydrogenizer | 2123.30 | 761.10 | €/$kW_{H2}$ | 1.00 | 20 |
| Dehydrogenizer | 1140.00 | 408.60 | €/$kW_{H2}$ | 1.00 | 20 |
| Low-pressure compressor | — | 1716.71 | €/$kW_p$ | 1.00 | 25 |
| High-pressure compressors | 560.00 | 1329.80 | €/$kW_p$ | 1.00 | 25 |

| Components | Efficiency | |
|---|---|---|
| Inverter | | 97% |
| Lithium-ion battery | $\eta_{\text{ch. and dis.}}$ | 95% |
| | Self-discharge | 0.01%/h |
| Redox flow battery | $\eta_{\text{ch. and dis.}}$ | 86.6% |
| PEM fuel cell | $\eta_{el}$ | 55% |
| PEM electrolysis | $\eta_{el}$ | 70% |
| rSOC electrolysis mode (w/o heat integration) | $\eta_{H_2}$ | 73.2% |
| rSOC fuel cell mode | $\eta_{H_2}$ | 45% |
| | $\eta_{el}$ | 35% |
| Heat pump | $COP_{min}$ | 2.86 |
| | $COP_{max}$ | 7 |
| Thermal storage | $\eta_{\text{ch. and dis.}}$ | 99% |
| | Self-dischsrge | 0.1%h |
| Electrical heater | $\eta_{el}$ | 98% |
| Heat exchanger/ | $\eta$ | 99.5% |

## References


[1] F. Contino, S. Moret, G. Limpens, H. Jeanmart, Whole-energy system models: the advisors for the energy transition, Prog. Energy Combust. Sci 81 (2020) 100872, https://doi.org/10.1016/j.pecs.2020.100872.

[2] O. Omoyele, et al., Increasing the resolution of solar and wind time series for energy system modeling: a review, Renew. Sustain. Energy Rev. (2024) 113792, https://doi.org/10.1016/j.rser.2023.113792.

[3] M. Hoffmann, L. Kotzur, D. Stolten, M. Robinius, A review on time series aggregation methods for energy system models, Energies 13 (3) (2020) 641, https://doi.org/10.3390/en13030641.

[4] P. Lopion, P. Markewitz, M. Robinius, D. Stolten, A review of current challenges and trends in energy systems modeling, Renew. Sustain. Energy Rev. 96 (2018) 156–166, https://doi.org/10.1016/j.rser.2018.07.045.

[5] D.F. Dominković, J.M. Weinand, F. Scheller, M. D'Andrea, R. McKenna, Reviewing two decades of energy system analysis with bibliometrics, Renew. Sustain. Energy Rev. 153 (2022) 111749, https://doi.org/10.1016/j.rser.2021.111749.

[6] K. Hacatoglu, I. Dincer, M. Rosen, A new model to assess the environmental impact and sustainability of energy systems, J. Clean. Prod. 103 (2015) 211–218, https://doi.org/10.1016/j.jclepro.2014.06.050.

[7] S. Rauner, M. Budzinski, Holistic energy system modeling combining multi-objective optimization and life cycle assessment, Environ. Res. Lett. 12 (12) (2017) 124005, https://doi.org/10.1088/1748-9326/aa914d.

[8] H.-K. Ringkjøb, P.M. Haugan, I.M. Solbrekke, A review of modelling tools for energy and electricity systems with large shares of variable renewables, Renew. Sustain. Energy Rev. 96 (2018) 440–459, https://doi.org/10.1016/j.rser.2018.08.002.

[9] J.M. Weinand, et al., Global LCOEs of decentralized off-grid renewable energy systems, Renew. Sustain. Energy Rev. 183 (2023) 113478, https://doi.org/10.1016/j.rser.2023.113478.

[10] H. Pandžić, Y. Dvorkin, Y. Wang, T. Qiu, D.S. Kirschen, Effect of time resolution on unit commitment decisions in systems with high wind penetration, in: 2014 IEEE PES General Meeting| Conference & Exposition, 2014, IEEE, pp. 1–5. doi: https://doi.org/10.1109/PESGM.2014.6939548.

[11] S. Pfenninger, I. Staffell, Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data, Energy 114 (2016) 1251–1265, https://doi.org/10.1016/j.energy.2016.08.060.
[12] I. Staffell, S. Pfenninger, Using bias-corrected reanalysis to simulate current and future wind power output, Energy 114 (2016) 1224–1239, https://doi.org/10.1016/j.energy.2016.08.068.
[13] I. Gonzalez-Aparicio, A. Zucker, F. Careri, F. Monforti, T. Huld, J. Badger, EMHIRES dataset: wind and solar power generation, Zenodo (2021), https://doi.org/10.2760/044693.
[14] Open power system data. https://data.open-power-system-data.org/time_series/2020-10-06 (accessed November 9, 2023).
[15] H. Bloomfield, D. Brayshaw, ERA5 derived time series of European aggregated surface weather variables, wind power, and solar power capacity factors: hourly data from 1950-2020, 2021. doi: 10.17864/1947.000321.
[16] H. Bloomfield, D. Brayshaw, A. Charlton-Perez, MERRA2 derived time series of European country-aggregate electricity demand, wind power generation and solar power generation, 2020.doi: 10.17864/1947.239.
[17] A. Troccoli, et al., The copernicus climate change service 'european climatic energy mixes, in: EMS Annual Meeting, 2017, vol. 14, pp. EMS2017-824. Available: https://minesparis-psl.hal.science/hal-01583161.
[18] M. Sengupta, Y. Xie, A. Lopez, A. Habte, G. Maclaurin, J. Shelby, The national solar radiation data base (NSRDB), Renew. Sustain. Energy Rev. 89 (2018) 51–60, https://doi.org/10.1016/j.rser.2018.03.003.
[19] M.J.M.L. Koivisto, J. Pablo, Pan-European wind and solar generation time series (PECD 2021 update), Technical University of Denmark. Collection (2022), https://doi.org/10.11583/DTU.c.5939581.v3.
[20] Z. Liu, Z. Deng, S. Davis, P. Ciais, Monitoring global carbon emissions in 2022, Nat. Rev. Earth Environ. 4 (4) (2023) 205–206, https://doi.org/10.1038/s43017-023-00406-z.
[21] U. Gstöhl, S. Pfenninger, Energy self-sufficient households with photovoltaics and electric vehicles are feasible in temperate climate, PLoS One 15 (3) (2020) e0227368.
[22] K. Nyarko, J. Whale, T. Urmee, Drivers and challenges of off-grid renewable energy-based projects in West Africa: a review, Heliyon (2023), https://doi.org/10.1016/j.heliyon.2023.e16710.
[23] M. Kleinebrahm, J.M. Weinand, E. Naber, R. McKenna, A. Ardone, W. Fichtner, Two million European single-family homes could abandon the grid by 2050, Joule 7 (11) (2023) 2485–2510, https://doi.org/10.1016/j.joule.2023.09.012.
[24] H. Gangammanavar, S. Sen, V.M. Zavala, Stochastic optimization of sub-hourly economic dispatch with wind energy, IEEE Trans. Power Syst. 31 (2) (2015) 949–959, https://doi.org/10.1109/TPWRS.2015.2410301.
[25] N. Troy, D. Flynn, M. O'Malley, The importance of sub-hourly modeling with a high penetration of wind generation, in: 2012 IEEE power and energy society general meeting, 2012, IEEE, pp. 1–6. doi: 10.1109/PESGM.2012.6345631.
[26] C. O'Dwyer, D. Flynn, Using energy storage to manage high net load variability at sub-hourly time-scales, IEEE Trans. Power Syst. 30 (4) (2014) 2139–2148, https://doi.org/10.1109/TPWRS.2014.2356232.
[27] I.D. Lopez, D. Flynn, M. Desmartin, M. Saguan, T. Hinchliffe, Drivers for sub-hourly scheduling in unit commitment models, in: 2018 IEEE Power & Energy Society General Meeting (PESGM), 2018, IEEE, pp. 1–5. doi: 10.1109/PESGM.2018.8586262.
[28] M.A. Meybodi, L.R. Santigosa, A.C. Beath, A study on the impact of time resolution in solar data on the performance modelling of CSP plants, Renew. Energy 109 (2017) 551–563, https://doi.org/10.1016/j.renene.2017.03.024.
[29] M. Ernst, J. Gooday, Methodology for generating high time resolution typical meteorological year data for accurate photovoltaic energy yield modelling, Sol. Energy 189 (2019) 299–306, https://doi.org/10.1016/j.solener.2019.07.069.
[30] M.J. Mayer, Effects of the meteorological data resolution and aggregation on the optimal design of photovoltaic power plants, Energ. Conver. Manage. 241 (2021) 114313, https://doi.org/10.1016/j.enconman.2021.114313.
[31] J. Deane, G. Drayton, B.Ó. Gallachóir, The impact of sub-hourly modelling in power systems with significant levels of renewable generation, Appl. Energy 113 (2014) 152–158, https://doi.org/10.1016/j.apenergy.2013.07.027.
[32] M. Kazemi, P. Siano, D. Sarno, A. Goudarzi, Evaluating the impact of sub-hourly unit commitment method on spinning reserve in presence of intermittent generators, Energy 113 (2016) 338–354, https://doi.org/10.1016/j.energy.2016.07.050.
[33] A. Zurita, C. Mata-Torres, J.M. Cardemil, R.A. Escobar, Assessment of time resolution impact on the modeling of a hybrid CSP-PV plant: a case of study in Chile, Sol. Energy 202 (2020) 553–570, https://doi.org/10.1016/j.solener.2020.03.100.
[34] J.E. Bistline, The importance of temporal resolution in modeling deep decarbonization of the electric power sector, Environ. Res. Lett. 16 (8) (2021) 084005, https://doi.org/10.1088/1748-9326/ac10df.
[35] T. Kërçi, J. Giraldo, F. Milano, Analysis of the impact of sub-hourly unit commitment on power system dynamics, Int. J. Electr. Power Energy Syst. 119 (2020) 105819, https://doi.org/10.1016/j.ijepes.2020.105819.
[36] M. Hofmann, G. Seckmeyer, Influence of various irradiance models and their combination on simulation results of photovoltaic systems, Energies 10 (10) (2017) 1495, https://doi.org/10.3390/en10101495.
[37] A. Villoz, B. Wittmer, A. Mermoud, M. Oliosi, A. Bridel-Bertomeu, S. PVsyst, A model correcting the effect of sub-hourly irradiance fluctuations on overload clipping losses in hourly simulations, in: 8th World Conference on Photovoltaic Energy Conversion, 2022. [Online]. Available: https://www.pvsyst.com/wp-content/uploads/2023/01/PVsyst_SubHourlyClipping_WCPEC8_2022.pdf.
[38] A.V. Klokov, E.Y. Loktionov, Temporal resolution of input weather data strongly affects an off-grid PV system layout and reliability, in: Solar, 2023, vol. 3, no. 1: MDPI, pp. 49–61. doi: 10.3390/solar3010004.
[39] K. Knosala, et al., Hybrid hydrogen home storage for decentralized energy autonomy, Int. J. Hydrogen Energy 46 (42) (2021) 21748–21763, https://doi.org/10.1016/j.ijhydene.2021.04.036.
[40] T. Groß, K. Knosala, M. Hoffmann, N. Pflugradt, D. Stolten, ETHOS. FINE: A Framework for Integrated Energy System Assessment, arXiv preprint arXiv: 2311.05930, 2023.
[41] L. Welder, D.S. Ryberg, L. Kotzur, T. Grube, M. Robinius, D. Stolten, Spatio-temporal optimization of a future energy system for power-to-hydrogen applications in Germany, Energy 158 (2018) 1130–1149, https://doi.org/10.1016/j.energy.2018.05.059.
[42] S. Leva, A. Nespoli, S. Pretto, M. Mussetta, E. Ogliari, Photovoltaic power and weather parameters, IEEE Dataport, September 23, 2020, doi: 10.21227/42v0-jz14.
[43] Y. Riffonneau, S. Bacha, F. Barruel, S. Ploix, Optimal power flow management for grid connected PV systems with batteries, IEEE Trans. Sustain. Energy 2 (3) (2011) 309–320, https://doi.org/10.1109/TSTE.2011.2114901.
[44] N. Pflugradt, U. Muntwyler, Synthesizing residential load profiles using behavior simulation, Energy Proc. 122 (2017) 655–660, https://doi.org/10.1016/j.egypro.2017.07.365.
[45] N.D. Pflugradt, Modellierung von wasser und energieverbräuchen in haushalten, 2016.
[46] L. Kotzur, P. Markewitz, M. Robinius, D. Stolten, Kostenoptimale Versorgungssysteme für ein vollautarkes Einfamilienhaus, Internationale Energiewirtschaftstagung 10 (2017) 1–14.
[47] M. Hoffmann, L. Kotzur, D. Stolten, The Pareto-optimal temporal aggregation of energy system models, Appl. Energy 315 (2022) 119029, https://doi.org/10.1016/j.apenergy.2022.119029.
[48] M. Hoffmann, J. Priesmann, L. Nolting, A. Praktiknjo, L. Kotzur, D. Stolten, Typical periods or typical time steps? A multi-model analysis to determine the optimal temporal aggregation for energy system models, Appl. Energy 304 (2021) 117825, https://doi.org/10.1016/j.apenergy.2021.117825.
[49] W. Gorman, The quest to quantify the value of lost load: a critical review of the economics of power outages, Electr. J. 35 (8) (2022) 107187, https://doi.org/10.1016/j.tej.2022.107187.
[50] T. Schröder, W. Kuckshinrichs, Value of lost load: an efficient economic indicator for power supply security? A literature review, Front. Energy Res. (2015) 55, https://doi.org/10.3389/fenrg.2015.00055.
[51] M.A.C. Hoffmann, Temporal aggregation methods for energy system modeling, Faculty 4 – Mechanical Engineering, vol. PhD, no. RWTH-2023-06886, pp. XXX, 341, Oral Examination: 01.12.2022 2023, doi: 10.18154/RWTH-2023-06886.
[52] T. Kannengießer, et al., Reducing computational load for mixed integer linear programming: an example for a district and an island energy system, Energies 12 (14) (2019) 2825, https://doi.org/10.3390/en12142825.
[53] B. Singh, O. Rehberg, T. Groß, M. Hoffmann, L. Kotzur, D. Stolten, Budget-cut: introduction to a budget based cutting-plane algorithm for capacity expansion models, Optim. Lett. 16 (5) (2022) 1373–1391, https://doi.org/10.1007/s11590-021-01826-w.