

Article

Design of Energy Communities and Data-Sharing: Format and Open Data

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Abstract: Governments are promoting energy community (EC) policies to encourage joint investment and the operation of shared energy assets by citizens, industries, and public authorities, with the aim of promoting economic, social, and environmental benefits. However, ECs require appropriate planning and energy management strategies, which require data that are rarely clean and well-structured. Data providers rarely adhere to a common format for data sharing, which hinders the development of ECs. As the number of ECs is expected to grow significantly, this poses significant issues for stakeholders to quickly and efficiently develop projects. To address this issue, in this paper we propose a literature-based analysis and classification to derive the major data needs for EC planning, as well as a template format for data sharing. Our literature review on ECs successfully identifies the main data required to properly describe this system and its components. Their classification further clarifies that data structures shall account for tabular-like data of various types and flexible dimensionality, or cardinality. A public release of an open dataset for a case study in Pisa, Italy is also provided, supported by realistic or real data for testing the sizing and operation of ECs. The results suggest that data standard practices are needed, and this paper can lay the foundation for their standardization for ECs to fast-forward their deployment as support policy and technical decision-making.

Keywords: renewable energy communities (REC); renewable energy systems (RES); datasets; open data format; photovoltaic; user loads



Citation: Guerrazzi, E.; Thomopoulos, D.; Fioriti, D.; Mariuzzo, I.; Schito, E.; Poli, D.; Raugi, M. Design of Energy Communities and Data-Sharing: Format and Open Data. *Energies* **2023**, *16*, 6268. <https://doi.org/10.3390/en16176268>

Academic Editor: Marco Merlo

Received: 7 July 2023

Revised: 18 August 2023

Accepted: 19 August 2023

Published: 29 August 2023



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1. Introduction

1.1. Motivation

To cope with climate change, society shall undergo a “decarbonization process” to meet its needs with sustainable practices. Energy plays a critical role, and increasing the penetration of renewable sources is of utmost importance [1]. In recent years, decentralized energy production, also using renewable energy sources (RESs), has risen attention as a viable option to support energy transition, especially under the energy community (EC) paradigm. In ECs, citizens, small consumers, and public authorities can group together, collectively participate in common energy investments, jointly coordinate to align demand and consumption supported by decentralized energy assets, and promote a positive environmental and social impact on local communities [2]. Generally, to reach high levels of sustainability, ECs exploit distributed RESs, providing cost-effective clean energy to the participants, reducing energy losses and carbon emissions. This type of EC is classically known as the renewable energy community (REC). Interest is increasing regarding the

development of the optimal planning, design, and operation of ECs, to meet the objectives of sustainability or the reduction in energy demands of these entities while preserving users satisfaction. However, the data to feed the mathematical models necessary for this relevant optimization procedure are rarely available, as well as their formatting characteristics. Identifying the key data of the energy systems mostly used in EC context; collecting details on their environmental, economic, and social impact [3]; and then developing a proper format to foster their sharing and implementation in optimization analyses would be advantageous for the scientific community and support multi-objective studies, as well as the development and validation of energy models and optimization strategies. However, limited studies have covered this topic.

The study of ECs involves the needs for multidisciplinary skills involving various aspects of technical, social, and economic considerations [4,5]. As a result, there are different approaches and methodologies for studying and analyzing these communities that overall need to be quantified. While each project or research study related to ECs may vary significantly, it is the role of the developer or modeller to capture the main characteristics of the system and quantify them to appropriately feed decision tools for energy planning. Given that no data standardization is available, issues of interpretability of data and duplication of data handling are arising.

To promote standardization and facilitate comparison among studies, we propose a first literature-based abstract classification of the data needs for energy modeling in ECs while also proposing a standardized data format for collecting and reporting information related to ECs. To accomplish this, a literature review about energy communities is conducted and analyzed to identify the main characteristics required for techno-economic and user behavior analysis. Moreover, we created and shared an open dataset by collecting real and realistic data about the characteristics of a possible EC located in Pisa, Italy.

This effort is expected to lay the foundations for a common data structure that can facilitate data sharing, analysis, and faster decision making. To the best of the author's knowledge, this represents the pioneering effort in this direction within the existing literature.

1.2. Literature Analysis

The literature analysis is structured as follows. First, we provide an overview about ECs and their adoption in recent years. Secondly, we discuss the state of the art of techno-economic modeling for ECs. Finally, we present the available datasets related to ECs, to be used for further research and analysis works in this field.

1.2.1. Energy Communities Adoption

In recent decades, renewable energy sources and energy efficiency have been identified as key drivers for achieving a decarbonized energy system [6]. The European Union has been working towards a sustainable energy system and society through a set of directives, including the clean energy package. In this context, renewable energy communities (RECs) have received particular attention, as defined by the Renewable Energy Directive REDII 2018/2001 [7] and the Electricity Market Directive 2019/944 [8]. An REC is a group of residential or industrial users whose participation should improve social welfare and achieve environmentally friendly goals as a non-profit entity. Users can choose their energy provider and express their desired electricity purchase price while participating in electric markets through demand side management (DSM) or demand response (DR) programs. Users can join or leave the community together with their personal point of delivery (POD), as a form of further flexibility. However, crucial aspects like technical skills of community members, the ownership of assets, and criteria for fair benefits sharing must be considered. Regarding Europe, connecting ECs in Sub-Saharan Africa can improve access to energy facilities and promote a renewed way of thinking about energy resources to tackle energy injustice [9]. In Latin America and the Caribbean, adequate access to education is crucial for local communities, researchers, and policy makers to ensure sustainable renewable energy projects and the preservation of biodiversity [10].

1.2.2. Techno-Economic Modeling

The modeling of energy communities can benefit from the literature on energy systems; while ECs are not only a technical system, social, organizational, and political considerations cannot be disregarded [11]. Many studies have focused on the optimal planning of the entire community as a whole, with economic objectives [12,13]. However, EC policies are explicitly promoting the involvement of citizenship in energy matters to promote environmental, social, and economic impact [6], and these aspects are increasingly being considered in EC planning [5], alongside the fair redistribution of the benefits across the whole community [4]. Various technologies, components, and sizes of community have been proposed, which imply different data requirements and solving techniques [11]. However, the level of complexity in which components, users, and their interactions are modeled must be balanced between computational time and the accuracy of the results. The most widely used technique for energy systems modeling and optimization is mixed integer linear programming (MILP) [14], but the larger the problem, the larger the computational complexity. Research studies have investigated the sizing and optimal planning of electrical assets, as well as the concept of exit clauses and different mechanisms for sharing benefits among members [4,15]. Other studies have explored internal energy transactions between users, including an environmental objective in the methodology [16]. Additionally, some authors have proposed an energy hub model that considers both electrical and thermal renewable assets for sizing and management [17]. On the other hand, characterizing the socio-economic preferences of users in ECs is notoriously challenging [5], and indeed social science research have been widely addressing this topic, e.g., by means of surveys [18]. Those techniques can be valuable for estimating the preferences and parameters of energy modeling to successfully perform comprehensive socio-economic and environmental planning of a community. While methodologies vary greatly, the input data required for the different tools are often similar. To facilitate data sharing and lay the foundations for further data standards, in this study we first propose an analysis of the major technologies and the main parameters needed by energy modeling techniques for optimizing EC.

1.2.3. Available Datasets

This section presents report papers dealing with datasets covering a wide range of aspects related to ECs, such as their energy generation and consumption profiles, socio-economic and environmental impacts, and the technical and economic performance of different energy technologies and solutions, with the aim of identifying the key elements that can be used for further research and development activities in this field. The paper by [19] provides a dataset focused on Norwegian energy communities. The dataset includes various types of data, such as household consumption data obtained from smart meter measurements and divided into consumer groups, appliance consumption data collected from Norwegian households, electric vehicle data related to charging patterns, simulated photovoltaic power generation data based on temperature and irradiance data sets, and wholesale electricity prices. All datasets are filtered by season, weekday/weekend, and time segment and are fitted to either a normal, exponential, or log-normal distribution. On the other hand, the authors in [20] publicly reviewed available datasets, tools, and models that can be used to optimize the design and operation of local energy communities (LECs). They also provided guidelines for different roles in real-world LECs, including aspiring and existing LECs. The article highlights the importance of open source datasets, tools, and models in grounding expectations and providing visibility on future energy and cash flows for LECs and other stakeholders. It also points out some of the limitations in currently available open source resources, e.g., the limited geographical availability of electricity demand datasets, and suggests future research directions, e.g., implementing a more holistic framework for integrating different elements of an LEC. The study [21] provides valuable information for investigating a dataset about electrical power consumption data and load profiles for several major household appliances in the US, including refrigerators, air conditioners, and washers. The data, measured in one-second intervals, is

available online and intended for use by researchers to develop realistic load models and analyze demand response algorithms for home energy management. Another recent data document [22] discusses the construction of a data set of the energy consumption behavior of a residential community, including photovoltaic generation and appliance usage profiles. The dataset was based on real data collected from 50 residential households and a public building. The article explains the process of gathering and normalizing the data and randomly attributing renewable solar energy to some households. The dataset can be used to examine and prove certain models related to the behavior of energy consumption. It may be useful for researchers studying renewable energy communities or distributed energy resources in general.

The proposed literature analysis highlights that existing works have focused on gathering data for ECs, but limited research has been focused on identifying the needed input data for sizing ECs.

1.3. Contributions and Organization of the Paper

This study contributes to the scientific literature by (a) identifying the major input quantities needed for sizing ECs; (b) classifying them; and (c) drawing guidelines for a data format, also including a practical case study for a realistic case study in Pisa, Italy. Based on a wide literature analysis, we describe the main components used in ECs, their main parameters, and their dimensionality to properly characterize the technical, economic, environmental, and social characteristics needed for energy planning. The analysis is functional to characterize the type and dimensionality of data, to describe the abstract data structure for ECs and requirements of dataformats to guide data collection, and the development of data standards. Moreover, we also present an open dataset obtained through real data from several sources that researchers can use for further studies and as a reference instance for algorithm benchmarking. This is expected to lay the foundations for guidelines on data format and sharing that is highly needed for interoperability and the widespread deployment of ECs. Considering privacy and copyright considerations, certain data have been intentionally perturbed. Consequently, in the ensuing sections, we will discuss data that are referred to as realistic, denoting data that have been subject to controlled alterations for specific reasons.

The paper is structured as follows: Section 2 describes the main assets of ECs and their main parameters, Section 3 introduces the proposed data structure, and in Section 4 conclusions are drawn.

2. Modeling of Energy Communities

In the following, we describe the features of the most useful parameters and data for modeling a generic EC while classifying their cardinality to lay the foundations for data platforms. In doing so, we first identified the different quantities and technologies needed for optimizing ECs, such as user load profiles and renewables production. Then, we reviewed the existing literature on RES and extrapolated their most relevant parameters in modeling an EC. Indeed, to the best of the authors' knowledge, there is no standard data format across ECs. These parameters have been divided by topic, along with a brief description and a summary table. Moreover, contrary to the literature, we also included the classification of technologies and the cardinality of the information to store that are needed when dealing with data formats. Each table includes columns such as the name of the parameter in the proposed data format, and cardinality, representing the dimensionality of the parameter to facilitate specific parsing. If a parameter α has a cardinality of $n \times m \times o$, the corresponding data will be organized in a multidimensional matrix of size $n \times m \times o$. If α is absent, the information is considered to be a scalar value. In the following sections, we explain how to represent such a data matrix in the proposed format. Furthermore, there are columns for description, unit, value, and ref, where value reports the range used in the proposed dataset (see Section 3 for further details).

2.1. Generic Parameters

This section provides an overview of the general parameters used to contextualize the subsequent data-driven modeling of all the elements involved in designing ECs. These parameters are provided in Table 1.

The first parameter we considered is the temporal granularity Δt of all the data, which is needed to capture the variability of renewable sources and load. For example, setting $\Delta t = 1$ means that each consideration about user loads, PV generations, etc., is made every minute.

To avoid handling a massive number of data, such as for every day of the year, it may be advantageous to select a subset of relevant and representative periods within the analyzed time-frame. In this context, T represents the number of intervals considered in the analysis. The starting date and the number of time-steps of every interval t are, respectively, given by S_t and D_t . For the sake of brevity in the subsequent dissertation, we denote \bar{T} as the sum of D_t over all intervals: $\bar{T} = \sum_{i=1}^T D_t$.

The generic parameters include the latitude λ and longitude ϕ , expressed in the degree and comma notation, which serve to geolocate the EC.

Furthermore, the number of users/households N in the EC is taken into account. Another crucial aspect in managing an EC is the presence of prosumers among the users. A prosumer refers to an energy user who can act as both a producer and consumer of electricity. Prosumers generate their own energy, typically using renewable sources like solar panels or wind turbines. They have the ability to consume power taken from the grid and, in other hours, feed the network with the electricity they have produced in excess with respect to their own needs. It is important to note that the energy production that a prosumer has self-consumed cannot be considered as part of the energy community. Consequently, it needs to be filtered out or treated separately in the collective energy management of the EC. Thus, the parameter PR_n is a boolean vector assigned to each user, with a value of 1 indicating a prosumer and 0 a passive user.

Finally, ρ_t represents the electricity price at time t .

Table 1. Generic parameters.

	Cardinality	Description	Unit	Value	Ref
Δt	-	Time-step	min	15 *	[5,23]
T	-	Number of temporal evaluation intervals	-	4 *	[24]
S_t	T	Starting date of every interval (ddmmyyyy, 00:00 UTC)	date	15/01/2019–15/10/2019 *	[25]
D_t	T	Number of time-steps Δt for each interval	-	288 *	-
\bar{T}	-	Size of an array of the discontinuous period over all the intervals	-	1152 *	-
λ	-	Latitude of the EC	° (Decimal degrees)	43.719 *	[26]
ϕ	-	Longitude of the EC	° (Decimal degrees)	10.427 *	[26]
N	-	Numbers of users in the EC	-	10 *	[5,24]
PR_n	N	Boolean attribute of user (1 if prosumer, 0 if passive user)	-	0 *	[24]
ρ_t	\bar{T}	Electricity price	€/kWh	39.4–99.2 *	[14,24,27]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.2. User Load Profiles

Electrical power consumption data and load profiles of household appliances are crucial elements for an EC because they drive the shared energy and consequently the business plan of the EC. Therefore, they are the key elements on which energy management algorithms are developed, such as demand response, whose usage is highly dependent on the social preferences of the household. Despite the fact that demand response mechanisms

are already well-diffused in large commercial and industrial customers, the same does not apply to the residential sector [21], where its deployment requires the flexible dispatch of a potentially large number of appliances, such as washing machines, clothes dryers, air conditioners, electric water heaters, electric ovens, dishwashers, and refrigerators. In the following, we detail the major inputs required for energy modeling, of which some parameters, e.g., equivalent costs of demand response, are subjective with regard to the user and may be estimated using surveys or social science analyses [18]. As this paper is focused on energy modeling, other papers may be more suited to the methodologies for estimating that number [11,28].

From an energy modeling perspective, the load profiles of households depend on the usage of their appliances. However, different appliances have different functioning mechanisms that can be classified as fixed, adjustable, and shiftable [29]. The different levels of flexibility offered by the different users have specific preferences. The fixed-load category includes appliances whose power consumption is constant and cannot be changed, such as for a fridge with a fixed temperature. In the adjustable-load category, we can find appliances whose operating condition is not fixed, i.e., the power consumption can vary according to the possibility of better ecologically satisfying the load (e.g., the eco-program in modern washers) or the cycle end time can vary according to the instantaneous power consumption, such as for the charge of electrical vehicles (EVs). Finally, the schedulable-load appliances are characterized by the flexibility of starting and ending their working cycle, with a fixed power consumption when they are switched on. Examples are washing machines, dishwashers, and microwaves. Schedulable loads also depend on the willingness of the users to change their preferred time window for using the appliance.

Table 2 resumes the main parameters that can be used to model user load profiles in an EC. The list of parameters start with the number of fixed, adjustable, and shiftable appliances for every user through parameters N_{fix} , N_{adj} , and N_{shf} . Fixed loads are the simplest user-loads from a modeling perspective since the only required parameter is P_{fix} for each fixed appliance. On the other hand, there are a few parameters involved in the modeling of an adjustable load. The boolean attribute ECO_{adj} represents the possibility for the considered load to have a more ecological alternative or not. In any case, the minimum and maximum power for satisfying the adjustable load are given by P_{adj}^{min} and P_{adj}^{max} , as well as the starting time S_{adj} and the maximum duration D_{adj} . In this way, it is possible to realistically and flexibly model the features of the adjustable load, i.e., according to the specific device and user wills. Regarding the shiftable loads, the consumed power P_{shf} is fixed but can be satisfied in one of the S time-slots, each one with its starting time S_s , duration D_s , and considering the duration of the shiftable load D_{shf} . Some of the most significant social aspects in the study of an EC can be observed precisely in the loads and preferences that users have in resizing or shifting their loads. Therefore, two continuous parameters ranging from 0.0 to 1.0 are introduced for each schedulable and adjustable load for every user [5]. These parameters, denoted as PRF_{adj} , encapsulate user preferences related to adjustable loads. A value of 0.0 signifies strong opposition towards load reduction, whereas a value of 1.0 indicates enthusiastic agreement to minimize the load as much as possible. On the other hand, PRF_{shf} represents preferences for shiftable loads and their respective time slots. A score of 0.0 signifies disapproval of the designated time slot, while a score of 1.0 reflects a strong liking for the slot.

In summary, these continuous parameters provide valuable insights into users' attitudes toward load management and temporal adjustments within the EC, shedding light on the intricate interplay of social dynamics and energy consumption.

We mention a few comprehensive data sources of user load data at an EC level (i.e., household), which have been used to partially or totally fill Table 2. These include data from the study of [21] and a free forum for the public to share their energy usage data developed by the National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory (LBNL), and Argonne National Laboratory [30].

Finally, the work of [31] produced a Matlab tool, which allows one to generate synthetic electricity load profiles of houses using a consumer load model, considering the Stockholm region of Sweden. The user can change select model parameter values and generate data for different time resolutions and periods.

Table 2. User load parameters.

	Cardinality	Description	Unit	Value	Ref
N_{fix}	N	Number of fixed-load appliances	-	1 *	[5]
N_{adj}	N	Number of adjustable-load appliances	-	1 *	[5,32–34]
N_{shf}	N	Number of shiftable-load appliances	-	1 *	[5,25]
ECO_{adj}	$N \times N_{adj}$	Boolean attribute of adjustable load (1 if eco available, 0 otherwise)	-	0 *	-
P_{fix}	$N \times N_{fix} \times \bar{T}$	Fixed load power	W	0–5312 *	[21]
E_{adj}	$N \times N_{adj} \times \bar{T}$	Adjustable load required energy	Wh	0–1323 *	[35]
p_{adj}^{min}	$N \times N_{adj} \times \bar{T}$	Minimum adjustable load power	W	0–4499 *	[32,34–36]
p_{adj}^{max}	$N \times N_{adj} \times \bar{T}$	Maximum adjustable load power	W	0–6087 *	[32,34–36]
PRF_{adj}	$N \times N_{adj}$	Preference of adjustable load to be reduced	-	0.0–1.0	[5]
P_{shf}	$N \times N_{shf}$	Shiftable load power	W	800–5200 *	[25]
S_{adj}	$N \times N_{adj}$	Starting time of adjustable-load	date	08:00–17:40 *	[32,34,36]
D_{adj}	$N \times N_{adj}$	Maximum duration of adjustable load	min	20–180 *	[32,34,36]
S	$N \times N_{shf}$	Number of time-slots for a shiftable load	-	1 *	[5,25,33]
S_s	$N \times N_{shf} \times S$	Starting time of time-slot	date	6:30–19:30 *	[5,25,33]
D_s	$N \times N_{shf} \times S$	Duration of time-slot for shiftable load	min	40–450 *	[5,25]
D_{shf}	$N \times N_{shf} \times S$	Duration of shiftable load	min	10–120 *	[5,25]
PRF_{shf}	$N \times N_{shf} \times S$	Preference of shiftable load	-	0.0–1.0	[5]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.3. Photovoltaic Generation Profiles

Photovoltaic systems (PV) are widely used RES in both residential and industrial applications, making them a fundamental technology within an EC. The modeling of PV generation began with the pioneering work of Evans [37] in 1981. Since then, more detailed models have been proposed to address the challenges of accurately capturing PV generation, including the use of metaheuristics to extract precise parameters from the complex and nonlinear characteristics of PV models [38]. This approach has gained significant attention and has proven effective in various scenarios, such as households, communities, and consumer behavior, enabling more accurate predictions of PV generation and the improved management of renewable energy resources. Table 3 summarizes the essential elements used in modeling PV generation.

The list of parameters starts with N_{PV} , which represents the number of available PV models, and Z_{PV} , indicating the number of installed systems for each PV model.

The power output of PV systems is strongly influenced by solar irradiance, which represents the amount of solar energy received per unit area. As the irradiance increases, the power production of the PV system also tends to rise. This relationship can be attributed to the physical properties of PV cells, which convert sunlight into electrical energy. When the solar irradiance is high, more photons strike the PV cells, leading to the increased generation of electron–hole pairs. Consequently, a greater amount of current is produced, resulting in higher power output. Conversely, when the irradiance is low, fewer photons interact with the PV cells, leading to a reduced generation of electron–hole pairs and a corresponding decrease in power output. Therefore, understanding the correlation between PV power and solar irradiance is crucial for accurately predicting and optimizing the performance of PV systems in various applications. Solar irradiance, in turn, consists of various components and is dependent on solar coordinates and the geometric angles of inclination. These factors contribute to its overall value and determine the amount of solar energy that reaches a specific location.

Table 3. PV generation parameters.

	Cardinality	Description	Unit	Value	Ref
N_{PV}	-	Number of available models of PV	-	2 *	-
Z_{PV}	N_{PV}	Number of PV already installed for every model	-	0 *	-
α_A	\bar{T}	Solar altitude angle	°	-67.3–67.8	[39]
α_S	\bar{T}	Solar azimuth angle	°	-179.6–178.9	[39]
β_{PV}	$N_{PV} \times \bar{T}$	Tilt angle of PV	°	55 *	[39]
γ_{PV}	$N_{PV} \times \bar{T}$	Azimuth angle of PV	40 *	°	[39]
b_{hi}	\bar{T}	Beam Horizontal Irradiance	W/m ²	0–800 *	[40,41]
d_{hi}	\bar{T}	Diffuse Horizontal Irradiance	W/m ²	0–316 *	[40,41]
r_i	\bar{T}	Reflected Irradiance	W/m ²	0 *	[40,41]
g_i	\bar{T}	Global Irradiance = $b_{hi} + d_{hi} + r_i$	W/m ²	0–943 *	[40,41]
T_{ext}	\bar{T}	Air temperature	°C	1.1–28.9 *	[41]
L_{PV}	N_{PV}	Length	m	1.67–1.99 *	[42]
W_{PV}	N_{PV}	Width	m	0.99 * [42]	
P_{PV}	$N_{PV} \times \bar{T}$	Effective PV power	kW	0–0.28 *	[43]
$P_{PV,nom}$	N_{PV}	Nominal power	kW	0.27–0.30 *	[44]
nop_{PV}	-	Number of extremes of a scale cost function	-	4 *	[45]
OP_{PV}	nop_{PV}	Power extremes of a scale cost function	kW	20 – > 1000	[45]
CI_{PV}	nop_{PV}	CAPEX cost	€/kW	700–1550	[46]
CO_{PV}	N_{PV}	Annual operating cost per P_{PV}	€/kW	10.5–23.25	[45]
EL_{PV}	-	Expected life	years	30 *	[47,48]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

The solar coordinates, including the altitude and azimuth solar angles α_A and α_S , describe the position of the sun relative to a given point on the Earth's surface. These coordinates, along with the geometric angles of inclination, i.e. the tilt and azimuth PV angles β_{PV} and γ_{PV} , play a crucial role in determining the intensity and distribution of solar radiation [49].

As already mentioned, solar irradiance encompasses various components, including beam, diffuse, and reflected irradiance. The global irradiance g_i represents the total power per unit area received on a surface and is obtained by summing these three components: beam irradiance b_{hi} , which results from direct solar rays; diffuse irradiance d_{hi} , which arises from scattered sunlight; and reflected irradiance r_i , which is the portion of solar radiation reflected off surfaces [40,41].

In the literature, in some cases, the cell temperature or at least the air temperature T_{ext} is also taken into account to provide a more accurate description of power. Incorporating ambient temperature data provides further insights into the overall thermal conditions that can impact the operation and power generation of the photovoltaic system. Accounting for these temperature factors enhances the accuracy of power modeling and enables a more comprehensive understanding of the performance of solar energy systems [40].

Dimensional data, specifically the length L_{PV} and width W_{PV} of the PV modules, can provide valuable information for system design and implementation. These parameters are valuable for considering spatial constraints and construction limitations.

The effective power produced by the PV system at time t is represented by P_{PV} , which may differ from the nominal power $P_{PV,nom}$. From an economic perspective, the cost of a PV system typically follows a step-wise trend, with the number of steps defined by nop_{PV} . Each step is characterized by the power extremes OP_{PV} and incurs a capital expenditure (CAPEX) cost CI_{PV} related to the investment, along with additional maintenance and operating costs CO_{PV} typically amounting to 2–5% of the CAPEX. The expected life of the PV system is given by EL_{PV} .

To estimate the time series of available production by a photovoltaic plant, some simulation tools have been proposed. A notorious example is the photovoltaic geographical information system (PVGIS) [50], developed by the Joint Research Centre of the European

Union, which allows users to estimate PV production by selecting or entering the location's latitude and longitude, along with parameters such as solar radiation database, PV technology, installed peak power, system loss, mounting position, slope, and azimuth. PVGIS provides simulated production data for download or viewing through its webpage. Another popular simulation tool for PV energy production is Renewable Ninja [51]. It enables users to estimate the performance of a PV system by specifying the location, system size, module type, tilt angle, and orientation. The tool utilizes weather data and satellite imagery to generate hourly estimates of energy production for a given location.

2.4. Wind Energy Generation Profiles

Electricity generation can also be obtained from wind turbines. According to [52], wind turbines are capable of converting the kinetic energy of wind into electrical energy. Comprising essential components such as the rotor, blades, hub, nacelle, and tower, wind turbines facilitate the capture and conversion of wind energy. The rotor and blades efficiently capture the wind's kinetic energy and convert it into rotational energy, which is subsequently transferred to a generator housed within the nacelle. Additionally, the nacelle incorporates a control system responsible for ensuring the turbine's optimal and safe operation.

Table 4 resumes the usable elements that are used for predicting wind generation in a certain zone.

Table 4. Wind energy generation predictors.

	Cardinality	Description	Unit	Value	Ref
N_{wt}	-	Number of available models of wind turbine	-	2 *	-
T_{wt}	N_{wt}	Number of wind turbines already installed for each model	-	0 *	-
U_{grd}	\bar{T}	Wind speed on W to E direction	m/s	-3.7–4.13 *	[53]
V_{grd}	\bar{T}	Wind speed on S to N direction	m/s	-2.21–4.96 *	[53]
V_{in}	N_{wt}	Minimum wind speed	m/s	1.5 *	[52,54]
V_{out}	N_{wt}	Maximum wind speed	m/s	52.5 *	[52,54]
V_r	N_{wt}	Reference wind speed	m/s	11 *	[52,54]
a, b, c, d, e, f	$6 \times N_{wt}$	Wind power coefficients	-	-	[52]
P_{wt}	N_{wt}, T	Effective wind power	kW	0–0.24 *	[52,54]
$P_{wt,nom}$	N_{wt}	Nominal power	kW	3–5 *	-
nop_{wt}	-	Number of extremes of a scale cost function	-	4	* [45]
OP_{wt}	nop_{wt}	Power extremes of a scale cost function	kW	500 – > 5000	[45]
CI_{wt}	nop_{wt}	CAPEX cost	€/kW	1100–1840	[46]
CO_{wt}	N_{wt}	Annual operating cost per P_{wt}	€/kW	200–330	[45]
DB_{wt}	N_{wt}	Noise	dB	45	[55]
EL_{wt}	-	Expected life	years	20 *	[56]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

In the modeling of wind turbine generation, a set of parameters plays a crucial role. These parameters include N_{wt} , denoting the number of available wind turbine models, and T_{wt} , indicating the number of installed wind turbines for each model.

Extensive research, as documented by [52–54], has highlighted several key factors influencing wind turbine energy production. These factors encompass the horizontal and vertical components of wind speed, represented by U_{grd} and V_{grd} , respectively. In a typical Cartesian coordinate system, the U_{grd} component represents the wind speed along the x-axis or the east–west direction. On the other hand, the V_{grd} component represents the wind speed along the y-axis or the north–south direction. If necessary, the Pythagorean theorem can be used to compute the effective value and direction of the wind speed components.

More sophisticated models consider also the parameters V_{in} , V_{out} , and V_r which play a significant role in characterizing the wind speed and its effects on electricity generation from wind turbines. V_{in} represents the minimum or cut-in wind speed. It is the threshold wind

speed at which a wind turbine starts to generate electricity. Below this value, the turbine may not produce any significant power output. V_{out} refers to the maximum or cut-out wind speed. It is the wind speed at which the wind turbine reaches its maximum power output and beyond which the turbine is shut down or curtailed for safety reasons. Operating the turbine at wind speeds higher than V_{out} may cause excessive stress on the turbine components. V_r denotes the reference wind speed. It is typically a design parameter specific to a particular wind turbine model or site. The reference wind speed represents the wind speed at which the turbine is designed to achieve its nominal or rated power output. It serves as a reference point for wind turbine performance evaluation and power curve characterization. These parameters, namely, V_{in} , V_{out} , and V_r , help define the operational range and performance characteristics of a wind turbine. They contribute to determining the start-up, maximum power, and shutdown conditions, ensuring the turbine operates efficiently and safely within specified wind speed ranges.

In some cases, non-linear curves with a few multiplicative coefficients, typically not exceeding 6, are also proposed in the literature. These parameters are often extracted from empirical tests. Therefore, six wind power coefficients (a, b, c, d, e, f) are considered sufficient to cover most of the functional forms commonly used in wind power modeling.

Notably, the effective power output at time t is indicated by P_{wt} , which may deviate from the nominal power $P_{wt,nom}$ under low wind speed conditions.

It is also crucial to consider the generation of noise DB_{wt} during wind turbine operation, particularly within the context of ECs. Noise emissions can potentially pose risks or discomfort to individuals, necessitating thorough examination and mitigation strategies.

Economically, the cost structure of wind turbine systems exhibits a step-wise trend, wherein nop_{wt} defines the number of steps. Each step encompasses specific power extremes OP_{wt} and incurs CAPEX costs CI_{wt} related to initial investments, as well as maintenance and operating expenses CO_{wt} . The projected lifespan of a wind turbine system is denoted by EL_{wt} .

It is worth mentioning that simulation tools have been developed to estimate the time-series of renewable production by wind, which can be used to feed EC planning tools. The first one is Wunderground [57], also known as Weather Underground, a popular online weather service that provides various meteorological information and forecasts. It collects weather data from a wide range of sources, including weather stations, personal weather stations, and meteorological organizations. Another one is Renewable Ninja [51], an online renewable energy assessment tool that provides data and analytics for various renewable energy resources, including wind energy. It offers insights into the wind potential of specific locations and helps assess the feasibility of wind energy projects. Finally, we cite AEOLIAN [58], an Italian web-based service that aims to provide accurate and reliable wind resource data for the Italian territory. It offers a database accessible through a user-friendly WebGIS tool, providing info on the general distribution of wind resources across Italy and helps identify areas suitable for wind energy exploitation.

2.5. Hydro-Electric

Hydroelectric power plants, specifically “run-of-river” systems, are a renewable energy technology that harnesses the kinetic energy of flowing water to generate electricity.

Table 5 summarizes the essential elements used in modeling hydro-electric generation.

In the context of ECs, the modeling of hydro-turbines involves considering the number of available hydro-turbine models, denoted as N_{hydro} , along with their respective installations within the community, represented by Z_{hydro} . The effective hydropower output, denoted as P_{hydro} , may deviate from the nominal power, $P_{hydro,nom}$, and is influenced by factors such as the effective flow rate, Q_{hydro} , and the minimum and maximum working flow rates, $Q_{hydro,min}$ and $Q_{hydro,max}$, respectively. Additionally, the net head height, H_{hydro} , which represents the vertical distance between the water source and the turbine, significantly impacts hydropower generation. The turbine efficiency, denoted as η_{hydro} , determines the effectiveness of converting kinetic energy into electrical power.

It is worth noting that run-of-river hydroelectric plants differ from cascade hydro generation. Run-of-river systems operate by utilizing the natural flow of a river without the need for large reservoirs, allowing water to flow freely through the turbine (see, e.g., [59]). On the other hand, cascade hydro generation involves a series of interconnected reservoirs with varying water levels, allowing for better control of water flow and storage (see, e.g., [60]). The choice between these approaches depends on various factors, including the availability of suitable water resources and the specific objectives of the renewable energy community. However, in the case of an energy community, the utilization of a run-of-river system is more plausible.

From an economic perspective, the cost of a hydro turbine system within an EC follows a step-wise trend, where the number of steps is defined by nop_{hydro} . Each step represents different power extremes, OP_{hydro} , and incurs a CAPEX cost, CI_{hydro} , which includes the initial investment and ongoing maintenance and operating costs, denoted as CO_{hydro} . The expected life of the hydro turbine system is given by EL_{hydro} .

Tools used for modeling hydro-electric power include HOMER Hydro Module [61] and RETScreen [62], which can be used to provide a comprehensive view by considering technical, financial, and environmental aspects.

Table 5. Hydro turbine parameters.

	Cardinality	Description	Unit	Value	Ref
N_{hydro}	-	Number of available models of hydro-turbines	-	1 *	-
Z_{hydro}	N_{hydro}	Number of already installed hydro-turbines	-	0 *	-
Q_{hydro}	\bar{T}	Effective flow	m ³ /s	7.96–69.6 *	[59]
$Q_{hydro,min}$	-	Minimum working flow	m ³ /s	5 *	[59]
$Q_{hydro,max}$	-	Maximum working flow	m ³ /s	30 *	[59]
H_{hydro}	-	Net head	m	14 *	[63]
η_{hydro}	-	Efficiency	-	70 *	[63]
P_{hydro}	$T \times N_{hydro}$	Effective hydro power	kW	0.08–0.30 *	[59]
$P_{hydro,nom}$	-	Nominal power	kW	0.3 *	[64]
nop_{hydro}	-	Number of extremes of a scale cost function	-	5 *	[64]
OP_{hydro}	nop_{hydro}	Power extremes of a scale cost function	kW	500 – > 10,000	[64]
CI_{hydro}	nop_{hydro}	Basically CAPEX cost	€ / kW	2300–6000	[46,64]
CO_{hydro}	N_{hydro}	Annual operating cost per P_{wt}	€ / kW	34.5–90	[65]
EL_{hydro}	-	Expected life	years	25 *	[66]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.6. Battery Energy Storage System Features

Battery Energy Storage Systems (BESS) are critical for the integration of renewable energy into the grid, and Lithium–ion (Li-ion) batteries are commonly used due to their high energy density, simple working principle, and decreasing costs. Among them, lithium–iron–phosphate (LiFePO₄) batteries are gaining popularity due to their higher stability, lower specific costs, and longer lifespan. Several studies include BESS modeling, but there is no standard approach. Five main types of BESS models are identified: ideal, charging/discharging efficiency, charging/discharging and self-discharging efficiency, degradation, and the simulation tool. Many studies limit their analysis to charging and discharging efficiencies, with only a few considering the self-discharging process or battery degradation. Further research is needed to integrate degradation phenomena in long-term studies [15,67–70].

Table 6 summarizes the essential elements used in modeling BESS usage in ECs.

Such table starts with N_{bs} which is the number of available models of BESS and B_{bs} , which indicates, for each model, the number of already installed BESS. According to the literature [71,72], the main features that influence the power modeling of BESS are the self-discharge, charge, and discharge coefficients η_{slf} , η_{ch} , η_{dch} . The effective charging or discharging power at time t is P_{ch} and P_{dch} , respectively. Moreover, the knowledge of the

initial state of charge SOC_0 is essential to model the subsequent states, knowing also the nominal capacity C_{bs_n} . As for the economical aspects, the cost of a BESS is typically given only from its purchase CI_{bs} .

Table 6. BESS parameters.

	Cardinality	Description	Unit	Value	Ref
N_{bs}	-	Number of available models of BESS	-	2 *	-
B_{bs}	N_{bs}	Number of BESS already installed for each model	-	1–4 *	-
η_{slf}	N_{bs}	Self-discharge coefficient	-	0.008–0.010 *	[71]
η_{ch}	N_{bs}	Charge coefficient	-	0.975–0.978 *	[71,72]
η_{dch}	N_{bs}	Discharge coefficient	-	0.920–0.950 *	[71,72]
P_{ch}	-	Charge power	kW	3.76–3.92 *	[71,72]
P_{dis}	-	Discharge power	kW	3.65–3.80 *	[71,72]
SOC_0	-	Initial state of charge	%	100 *	[73]
CI_{bs}	N_{bs}	Basically CAPEX cost	€/kWh	550–580	[5]
C_{bs_n}	N_{bs}	Nominal capacity	kWh	3.84–4.00 *	[74]
EL_{bs}	-	Expected life	years	15 *	[14]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.7. Heat Pumps

Decarbonizing thermal loads is classically difficult, due to the high requirements of the buildings and the limited number of options compared with solutions for electrical loads [75]; in the literature, this problem is recognized as a bottleneck [76]. Nowadays, the most widespread solution to reduce the fossil-fuel requirements for buildings involves electrically driven heat pumps, which can provide both cooling and heating loads to buildings. Focusing on heating loads, the heat is typically taken from an external source (e.g., outdoor air, ground-source, or water) and released in indoor spaces via a compression cycle using electricity. The most widespread typology of heat pumps is the air-source one, which exchanges energy with external air and provides heating/cooling for building through a thermal exchange with either indoor air or water-based terminal units. Heat exchangers and a vapor compressor are considered as a key technology to link the electric and thermal energy sectors [77]. During the last decades, their electricity-to-heat efficiency, known as COP (coefficient of performance), has increased, enabling the use of less electricity to provide the same thermal outputs. At the same time, their use fosters the exploitation of renewable energy sources: as an example, electrical energy provided by photovoltaic modules can be successfully employed to supply heating/cooling load through the compressor. In this way, it is possible to increase the rate of decarbonization in the building sector, which represents a high share of the final energy consumption. On the other hand, without a proper strategy to reduce electricity-related emissions, the employment of heat pump may not result competitive in the context of building loads, also because of the high operative costs of electrical energy compared with fossil fuels.

Integration of heat pumps in ECs is highly recommended for a twofold reason: they increase the share of self-consumption of electrical energy from RES, and they can also provide a flexible load to manage, avoiding mismatch between production and consumption. An additional increase in flexibility can be reached if thermal storages are used together with heat pumps: in this way, hot water provided during daytime (so when the production of RES is at its maximum) can be stored in thermal energy systems and then used during nighttime. However, there are limits in this flexible behaviour, depending on the thermal comfort experienced by the users. In some pieces of research [78,79], the proper operation of heat pumps has proven to mitigate over-voltage problems due to photovoltaic production.

Table 7 summarizes the essential elements used in modeling heat pumps.

To successfully integrate heat pumps into ECs, it is important to have data on the thermal loads and the efficiency of the heating generators. Thermal loads (both heating and cooling) can be monitored: they strongly depends on envelope characteristics, external climate and users' preference, so it is not possible to generalize. If a monitoring campaign is not achievable, dynamic simulation tools can be employed (e.g., TRNSYS, EnergyPlus). Then, the dynamic efficiency of the heat pump is also needed, to check the amount of electrical energy to run the compressor and evaluate the rate of self consumption by RES. Also in this case, having monitored data allows one to obtain a good correlation between loads and factors influencing the COP (e.g., temperature lift, capacity ratio).

If these data are not available, it is also possible to use models. Typically, COP can be evaluated using two different methods:

- Utilizing manufacturers' data to provide COP at different values of internal and external temperature and capacity ratio. A regression analysis is then performed to assess the system's performance for each combination of temperature and thermal load;
- Employing equations specified in technical standards [80,81]. These equations express the COP at full load as the product of the exergetic efficiency of the inverse thermodynamic cycle (η_{II}) and the ideal Carnot efficiency (COP_{id}). The influence of partial load conditions is evaluated through a reduction factor (f_{CR}).

Also the threshold values of operating ranges of heat pump should be known. Generally, heat pumps cannot properly operate at too low external temperatures or too high supply temperatures.

Table 7. Heat pump parameters.

	Cardinality	Description	Unit	Value	Ref
N_{HP}	-	Number of heat pump models available in the EC	-	1 *	-
Z_{HP}	N_{HP}	Number of installed heat pumps for each model	-	1 *	-
$Q_{nom,H}$	N_{HP}	Nominal capacity of the heat pump in heating mode	kW	200 *	[82,83]
$Q_{nom,C}$	N_{HP}	Nominal capacity of the heat pump in cooling mode	kW	200 *	[82,83]
Q_H	$N_{HP} \times \bar{T}$	Thermal load provided by the heat pump in heating mode	kW	0–192.3 *	[84]
Q_C	$N_{HP} \times \bar{T}$	Thermal load provided by the heat pump in cooling mode	kW	0–109.3 *	[84]
\bar{T}_H	$N_{HP} \times \bar{T}$	Supply fluid temperature in heating mode	K	50 *	[85]
\bar{T}_C	$N_{HP} \times \bar{T}$	Supply fluid temperature in cooling mode	K	10 *	[86]
T_{ext}	\bar{T}	Ambient temperature	K	−1.9–28.9 *	[50]
$COP_{nom,H}$	N_{HP}	Nominal coefficient of performance in heating mode	-	3.35 *	[82,83]
$T_{nom,H}$	N_{HP}	Nominal supply temperature in heating mode	K	45 *	[82,83]
$T_{nom,ext}$	N_{HP}	Nominal ambient temperature in heating mode	K	7 *	[82]
$COP_{nom,C}$	N_{HP}	Nominal coefficient of performance in cooling mode	-	3.51 *	[82,83]
$T_{nom,C}$	N_{HP}	Nominal supply temperature in cooling mode	K	7 *	[83]
$T_{nom,ext}$	N_{HP}	Nominal ambient temperature in cooling mode	K	35 *	[82]
CI_{HP}	N_{HP}	CAPEX cost	€/kW	700	[45,64]
EL_{HP}	-	Expected life	years	15 *	[87]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.8. Solar Thermal

Solar thermal collectors (also known as solar thermal) are devices converting solar energy into thermal energy, typically for domestic or small-commercial applications [45,64,88]. They are mainly used for space heating and domestic hot water; in some applications, the solar energy collected through them can also be used for cooling services, together with an absorption chiller, or for drying applications [45,64,89]. In this analysis, we focus only on solar collectors for heating and domestic hot water purposes, and for typical civil applications: in other words, we do not consider parabolic collectors, solar furnaces, and

solar towers for electricity production. Table 8 summarizes the essential elements used in modeling solar thermal collectors.

In civil applications, flat-type collectors are typically used. They consist of an absorber plate, tubes for the circulating fluid, and a glazing cover. The absorber has specific thermal and optical properties (high absorptance for solar radiation and low emissivity on infrared wavelength), to maximize the absorbed radiation (both beam and diffuse radiation), which are then transferred to the fluid circulating in the risers. A glazed cover is usually present in the front of the collector, to limit the thermal losses due to convection with ambient air. In mild-hot climates, the glazed cover may be absent.

Another type of solar thermal collector is the evacuated tube collector, which consists of an evacuated cylindrical tube with a heat pipe inserted into it. The use of a vacuum-sealed tube reduces the thermal losses, so this type of collector is characterized by high efficiency and high values of temperature that can be reached by the circulating fluid.

The optimal position for solar thermal depends on the roof where it is installed on. As a general rule of thumb, solar thermal should face south in the north hemisphere, with an inclination of the latitude of the location [90]. Of course, shadowing from other buildings or other orographic obstacles should be avoided.

Solar thermal collectors use either ambient air or water to deliver the thermal load to the building. In the former case, the collector is known as a solar air heater, and in the latter as a solar water heater. The main advantages to use air as heat transfer fluid are: no freezing/boiling problems, lower cost, and absence of expansion vessel. However, as the air heat transfer coefficient is lower than the water one, a higher flow rate is necessary to deliver the same thermal load, with the consequence on the collector surface and electrical energy at the fan. Using air allows one to directly warm up the indoor spaces; a heat exchanger is instead necessary to warm the water within a domestic hot water tank. Solar water heaters, instead, are not often used directly for space heating and domestic water purposes, due to the presence of antifreezing fluids mixed with air. Hot water tanks are used to store the warm water and use it in a following moment for domestic hot water or space heating purposes.

One of the most widespread models to evaluate efficiency of solar thermal has been provided by [90]: it uses the optical properties of the collector, the coefficients related to thermal losses, the ambient temperature, the solar radiation, and the inlet temperature. The presence of a thermal storage should be considered as influencing the overall performance of the system: see also Section 2.9. Also, TRNSYS, RETScreen, and Energy-Plus can be used to evaluate the delivered thermal energy and the efficiency of the solar thermal collectors.

Table 8. Solar thermal parameters.

	Cardinality	Description	Unit	Value	Ref
N_{ST}	-	Number of solar thermal collectors available in the EC	-	1 *	-
Z_{ST}	N_{ST}	Number of installed solar thermal collectors for each model	-	3 *	-
A_{ST}	N_{ST}	Area of installed solar thermal for each model	m ²	2.5 *	[82]
β_{ST}	N_{ST}	Tilt angle of installed solar thermal for each model	°	30.0 *	[91]
γ_{ST}	N_{ST}	Orientation angle of installed solar thermal for each model	°	0.0 *	[91]
b_{hi}	\bar{T}	Beam irradiance on the horizontal	W/m ²	0.0–735 *	[50]
d_{hi}	\bar{T}	Diffuse horizontal irradiance on the horizontal	W/m ²	0.0–295 *	[50]

Table 8. Cont.

	Cardinality	Description	Unit	Value	Ref
r_i	\bar{T}	Reflected irradiance on the horizontal	W/m ²	0.0 *	[50]
g_i	\bar{T}	Global irradiance on the horizontal	W/m ²	0.0–858 *	[50]
T_{ext}	\bar{T}	Ambient temperature	K	−1.9–28.9 *	[50]
T_{in}	$N_{ST} \times \bar{T}$	Inlet fluid temperature at each ST	K	13.6–71.5 *	[91]
\dot{m}	$N_{ST} \times \bar{T}$	Fluid flow rate for each ST	kg/s	0.0–3.3 *	[92]
c	N_{ST}	Specific heat capacity for the circulating fluid in each ST	kJ/kgK	4.19 *	[92]
η_0	N_{ST}	Optical efficiency of each ST	-	0.79 *	[82]
IAM	N_{ST}	Incidence angle modifier	-	0.94 *	[82]
α_1	N_{ST}	First factor for heat loss correction value	W/m ² K	3.59 *	[82]
α_2	N_{ST}	Second factor for heat loss correction value	W/m ² K ²	0.01 *	[82]
CI_{ST}	N_{ST}	CAPEX cost	€/collector	1200	[82]
EL_{ST}	-	Expected life	years	15 *	[93]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.9. Thermal Storage

Thermal energy storage (TES) is an important element for a renewable energy communities as it enables excess heat provided by renewable sources or by heat pumps to be stored for use during times of low energy production. Traditionally, TES has consisted of a large volume of water used to decouple the generation to the load, thus obtaining a double beneficial result: on one hand, this decreases the size of the heating and cooling generators; on the other hand, it exploits periods of low operating cost or high production from RES to meet the loads required in less convenient periods [94].

However, in recent years, the literature has reported many interesting results on various different TES-related topics, e.g., materials, optimal sizing and management. The first way to categorize TES considers the type of heat transfer and the storage material [95,96]:

- Considering the type of heat transfer, two concepts can be defined:
 - Active systems, where the thermal energy is stored using engineering systems, controlling the heat transfer through forced convection and mass flow rate;
 - Passive systems, where instead thermal energy is stored through natural convection, without specific control systems;
- Considering the storage material, two categories can be defined:
 - Sensible storage, which is the most common type of storage; among the used materials, the most widespread are water, air, rocks, sand, and building construction materials such as bricks and concrete;
 - Latent storage, which consists of materials storing thermal energy through a phase change, usually a solid-liquid phase change; these materials are known as phase change materials (PCMs).

A common application of TES is the integration with solar thermal: in the passive configuration, the thermal storage is closed to the solar collector; it takes advantage of the increasing temperature within the risers to move the warm water in the store. In larger systems, the thermal storage may be situated in other locations, far from the solar collectors, and using pumps to circulate the water. Another typical integration of TES is related to heat pumps: heating energy and cooling energy are provided by the thermal generator during periods with high COPs or high RES production, stored within the TES, and then used during peak loads.

Another novel technology is to use the building core itself as thermal storage [95]: some examples include the use of TES in double skin facades or suspended ceilings, also incorporating thermal activated materials.

The previous analyzed configurations refer to systems to be used on hourly or daily basis (the heat provided during daytime can be used during nighttime). In very large systems, however, it is possible to also store energy on a seasonal basis, exploiting solar energy provided during summer months during the winter period. This type of storage, known as seasonal thermal energy storage, can be used in areas with high building density, such as ECs. Even though various types of thermal storage systems exist, a common characteristic is their utilization of the ground, which allows for the construction of large-sized tanks or volumes. Examples include tank thermal storage, aquifer thermal storage, and borehole thermal storage.

The actual efficiency of a thermal storage within an EC depends on its size and its control; furthermore, the capital costs are factors strongly influencing the feasibility of TES introduction within a grid.

Table 9 summarizes the essential elements used in modeling TES.

The most common parameters used to model thermal storage (and assess its suitability) are the heat capacity of the storage material, its mass, the rate of charge and discharge (in other words, the power available to meet the load), and the temperature difference the storage is subject to. Tools used for modeling thermal storage include TRNSYS, EnergyPlus, and Matlab.

Table 9. Thermal storage parameters.

	Cardinality	Description	Unit	Value	Ref
N_{TS}	-	Number of thermal storages available in the EC	-	1 *	-
Z_{TS}	N_{TS}	Number of installed thermal storages for each model	-	1 *	-
V_{TS}	N_{TS}	Volume of each TS model	m ³	0.475 *	[97,98]
S_{TS}	N_{TS}	Surface of each TS model subject to thermal loss	m ²	9.0 *	[99]
$k_{boll,TS}$	N_{TS}	Heat loss coefficient for each TS model	W/K	2.49 *	[97,100]
$T_{TS,ext}$	$N_{TS} \times \bar{T}$	Temperature of the environment where the TS is installed	K	-1.9–28.9 *	[100]
c	N_{TS}	Specific heat capacity of the fluid within the TS	kJ/kgK	4.19 *	[97,100,101]
ρ	N_{TS}	Density of the fluid within the TS	kg/m ³	1000 *	[97,98,101]
T_{max}	N_{TS}	Maximum temperature to be reached inside the TS	K	80 *	[102]
λ_{TS}	N_{TS}	Latent heat of the phase-change material	kJ/kg	-	[98,101]
T_{PC}	N_{TS}	Melting temperature of the phase-change material	K	-	[98]
η_{HE}	N_{TS}	Efficiency of heat exchange from the helix to the bulk	-	0.65 *	[103]
$T_{TS,in,g}$	$N_{ST} \times \bar{T}$	Inlet temperature of the fluid from generator	K	13.6–76.5 *	[104]
$\dot{m}_{in,g}$	$N_{ST} \times \bar{T}$	Flow rate of the fluid from generator	kg/s	0–3.3 *	[105]
$T_{TS,in,l}$	$N_{ST} \times \bar{T}$	Inlet temperature of the fluid used for the load	K	15.0–25.0 *	[104]
$\dot{m}_{in,l}$	$N_{ST} \times \bar{T}$	Flow rate of the fluid used for the load	kg/s	0.0–0.2 *	[105]
CI_{TS}	N_{TS}	CAPEX cost	€/m ³	712.5	[106–108]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.10. Combined Cooling, Heating, and Power

Even if they generally use fossil fuels, combined cooling, heating, and power systems (CCHPs) can be successfully integrated within an energy community: the possibility of

providing electrical energy together with heating and cooling loads allows for the high overall efficiency of these systems and a strong reduction in carbon dioxide emissions. IEA research [109] has revealed that the global capacity of those systems is estimated to almost double up to 2030.

CCHP systems usually include a power generation unit (e.g., microturbines, internal combustion engines, and fuel cells), often fueled by natural gas; as a byproduct, the heat is recovered and used for many heating applications, even at different temperature levels. If only heating is recovered, these systems are known as combined heating and power (CHP) or cogenerators. The recovered heat can also be used in absorption chiller or heat pump to provide cooling load: these systems are CCHPs.

There are three typical operating modes of a CCHP [88]:

- The following electrical load: the fuel flow rate is chosen to meet the electrical load; the thermal load provided is partially recovered, depending on the actual users' requirements; in case of a surplus, the thermal energy is stored or wasted; and in case of a deficit, a backup thermal system is used;
- The following thermal load: the fuel flow rate is chosen to meet the buildings' thermal load; the electrical energy is used for the electrical requirement, which involves considering either to sell the surplus to the grid if exceeding the users' load or purchasing an additional amount of energy from the grid in case of deficit;
- The base load: the fuel flow rate is chosen to provide a fixed amount of electrical energy and thermal energy, which does not depend on the actual buildings' load.

Recently, renewable sources have also been used to fuel CCHP systems. As an example, Denmark [110] has increased the ratio of RES used in CHP from 20% to 64% in 30 years, mainly by using biomass. In some other cases, energy from sun or waste recovery is also used. In [111], the authors discuss the advantages of using biomass gasification as a fuel in small-scale CHPs. Among them, the most important one is the possibility of the exploitation of local biomass resources with high efficiency, providing both heating and electrical energy, differently from mere direct combustion, which only provides heating low at a very-low thermal efficiency. In [112], the authors discuss the techno-economic feasibility assessment of a CHP using municipal solid waste to provide heat and electricity for a university campus. The results show that a high amount of CO₂ emission can be saved through the use of this CHP.

The assessment of the feasibility of a CHP within a grid is strongly affected by its purchase cost, and the thermal and electrical loads it should meet, at least partially. In an EC, this evaluation is even more important, due to the presence of renewable sources, providing non-programmable energy, which should be used as a priority, then changing the instantaneous share of thermal/electrical energy needed from the buildings. As the cogeneration plant cannot overcome a minimum capacity ratio, the aleatory of RES can reduce the efficiency of CCHP, leading to energy waste or RES curtailment, as recognized by various pieces of research [113,114].

Table 10 summarizes the essential elements used in modeling CCHPs.

The main parameters used to model CCHPs include the provided electrical, the heating and cooling load, the electrical and thermal efficiencies, the level of temperatures the heat is recovered at, the fuel consumption rate, and the capacity factor. Tools used for modeling cogenerators include TRNSYS, EnergyPlus, and HOMER.

Table 10. Cogenerator parameters.

	Cardinality	Description	Unit	Value	Ref
N_{CCHP}	-	Number of CCHP systems available in the EC	-	1 *	-
Z_{CCHP}	N_{CCHP}	Number of installed CCHP systems for each model	-	1 *	-

Table 10. Cont.

	Cardinality	Description	Unit	Value	Ref
$T_{H,CCHP}$	$N_{T,CCHP}$	Levels of supply temperature delivered by each CCHP system	-	1 *	[115]
\dot{Q}_C	$N_{CCHP} \times \bar{T}$	Thermal energy recovered for cooling from each CCHP	kW	0.0 *	[116]
\dot{Q}_H	$N_{CCHP} \times N_{T,CCHP} \times \bar{T}$	Heat recovered from each CCHP for each level of supply temperature	kW	6.6–14.3 *	[117,118]
\dot{E}_{el}	$N_{CCHP} \times \bar{T}$	Electrical energy provided by each CCHP	kW	3.3–8.3 *	[117,118]
η_H	$N_{CCHP} \times \bar{T}$	Thermal efficiency of each CCHP for heat recovery	-	0.6–0.7 *	[116–118]
η_C	$N_{CCHP} \times \bar{T}$	Thermal efficiency of each CCHP for cooling	-	0.6–0.7 *	[116]
η_{el}	$N_{CCHP} \times \bar{T}$	Electrical efficiency of each CCHP	-	0.0 *	[116–118]
\dot{m}_{fuel}	$N_{CCHP} \times \bar{T}$	Fuel flow rate for each CCHP	kg/s	0.3 *	[116]
LHV_{fuel}	N_{CCHP}	Lower heating value of the flow rate for each CCHP	MJ/kg	13 *	[119]
CI_{CCHP}	N_{CCHP}	CAPEX cost	€/kW	37,589	[120,121]
EL_{CCHP}	-	Expected life	years	15 *	[122]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.11. Biomass and Other Thermal Generators

Backup thermal generators should be present in an energy community as it may be impossible or unfeasible to meet the overall thermal loads only with the previously mentioned systems: due to their intermittence and aleatory, solar thermal collectors may provide only a share of the load, especially in the daytime and in summer in the absence of thermal storages; heat pumps may operate in inefficient conditions, or even stop operating in particularly extreme external conditions.

Typical backup generators are boilers, providing heating load by fuel combustion. Nowadays, natural gas is the most widespread fuel used for heating: it represents more than 40% of the heating mix in the European Union and more than 60% in the United States [123]. If used in condensing boilers, efficiency can be around 100%.

However, to reach the goals of CO₂ reduction, the heating system should use low-emission fuels. Examples could be: a biomass source, a mixture of natural gas and hydrogen, and a mixture of natural gas and biogas.

Biomass, which is derived from organic materials, can certainly play a role in the context of reducing fossil-fuel use; however, its emission factor is quite high [124]. The direct combustion of biomass is the most widespread process; it contributes to 97% of the biomass use of energy production [125]. The efficiency of biomass boilers is, however, very low; besides, particular technologies are necessary to reduce NO_x and SO_x during the combustion process [111].

A mixture of natural gas and biogas, which is produced from raw biomass materials, or a mixture of natural gas and hydrogen, known as hydrogen-enriched natural gas, are also considered promising options in the heating sector. In particular, hydrogen can also be produced using renewable energy sources through electrolysis technology. This process is known as power-to-gas: electrical energy from RES is used to split water into hydrogen and oxygen, thus allowing for the injection in the gas grid: it can be used for a heating service, or the pipeline itself can act as an energy buffer [126].

Table 11 summarizes the basic elements used in modeling biomass.

Considering all the possible solutions that can be employed to provide heating, the main parameters include all the features of the fuel: its heating value, its consumption rate, and its efficiency in the combustion process.

Table 11. Biomass system parameters.

	Cardinality	Description	Unit	Value	Ref
N_B	-	Number of thermal generators available in the EC	-	1 *	-
Z_B	N_B	Number of installed thermal generators for each model	-	1 *	-
\dot{Q}_H	$N_B \times \bar{T}$	Heating load provided by each thermal generator	kW	0.0–14.8 *	[83]
η_H	N_B	Heating efficiency of each thermal generator	-	0.96 *	[124,127]
LHV_{fuel}	N_B	Lower heating value of the flow rate for each thermal generator	MJ/kg	13 *	[128]
CI_B	N_B	CAPEX cost	€/kW	6000	[106]
EL_B	-	Expected life	years	15 *	[129]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

2.12. Connection to Energy Networks

The users of the EC are generally connected to the electricity grid, yet other energy networks may apply, e.g., the gas infrastructure. The connection characteristics and the regulation in force may enable trading electricity using institutional markets and/or by means of private agreements within the members of the EC, which can play a role in the overall techno-economic and environmental performances of the community. In Table 12, the major parameters regulating the connection are reviewed and summarized. A number N_V of energy networks (usually electricity and gas) may be available to each user, which implies yearly costs due to the type of connection and energy flow. In particular, the type of contract and the maximum capacity of the connection are usually quantized with power values PC_V and specific costs OC_V . In particular, for each energy network, the construction costs CI_V for establishing the connection also apply. The energy flow is generally charged by various fees, the most notable being the purchase π_V^B and selling π_V^S prices, also including transport tariffs. Moreover, excise or taxes π_V^E on consumption apply. In the field of ECs, the so-called reward π_V^R , awarded to shared energy, applies as well. A Boolean variable $NET_{V,n}$ is assigned to each user and energy network (set to 1 if the energy network is available, and 0 otherwise).

Table 12. Connection to energy networks.

	Cardinality	Description	Unit	Value	Ref
N_V	-	Number of energy vectors	-	1 *	-
NCP_V	N_V	Number of available committed power capacities	-	1 *	-
$NET_{V,n}$	$N \times N_V$	Boolean attribute of every user and every energy vector (1 if energy vector available, 0 otherwise)	-	1 *	-
PC_V	$N_V \times NCP_V$	Available committed power capacities by vector	kW	3 *	[130]
OC_V	$N_V \times NCP_V$	Yearly cost for each committed power capacity	€/y	30 *	[4]
π_V^B	$N_V \times NCP_V \times \bar{T}$	Variable buying energy price	€/kWh	0.16 *	[4]
π_V^E	$N_V \times NCP_V \times \bar{T}$	Excise	€/kWh	0.02 *	[4]
π_V^S	$N_V \times NCP_V \times \bar{T}$	Selling energy price	€/kWh	0.05 *	[4]
π_V^R	$N_V \times NCP_V \times \bar{T}$	Reward to the community for the shared energy	€/kWh	0.10 *	[4]
CI_V	$N_V \times NCP_V$	Connection cost	€	500	[131]

* Refers to data sample at <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

3. Data Structure for Renewable Energy Communities

Based on the extensive literature analyses and other novel parameters introduced in Section 2, in the following we present a proposal of the data structure that captures the major inputs needed for modeling energy communities, including all the various electric and thermal assets involved, with the aim of overcoming the current lack of common data format across ECs. To guarantee the readability of the format by most software, we propose

a tabular format as shown in Figure 1 as a CSV file, where the first column and the first row pertaining to a specific data point contain the corresponding data label. This visual arrangement aims to improve the usability and accessibility of data.

The CSV is a very generic, flexible, and accessible file format that enables addressing different data dimensions and cardinalities, wherein the dimensions of the parameters are consistently indicated before the data itself. This versatility is exemplified by its utilization in various fields, as demonstrated in previous works like [132]. In the case of multidimensional matrices, they are projected into two-dimensional matrices. For example, a data set with dimensions of $n \times m \times o$ will be represented as o matrices of size $n \times m$ in the CSV format.

The data format encompasses diverse types of information, where certain details may be missing. Some data may appear redundant as they are interrelated. This design enables the integration of different data sources within a single unified format. In cases where a particular data point is not available, the corresponding element may be replaced with the symbol “-”.

A first dataset with real and realistic data, concerning a potential EC in Pisa and following the presented data format, is available in the GitHub repository <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023. The proposed case can be considered representative of the Italian scenario, since, according to the recent national regulation that is being entered in force, users may join and form ECs if they are served by the same primary substation [130]. This highlights the significant number of ECs that may be potentially created, which in turn leads to standardization needs. We mention that some of the proposed data are realistic due to privacy concerns. In these instances, the data have undergone slight manipulation to ensure coherence without compromising privacy rights.

An example with a temporal resolution (Δt) of 15 min and 4 intervals of 3 days and 10 consumers should be formatted as in Figure 1.

```

Δt;15;;;;;;
T;4;;;;;;
St;20190115;20190415;20190715;20191015;;;;;;
Dt;288;288;;;;;;
λ;43,719;;;;;;
φ;10,427;;;;;;
N;10;;;;;;
PRn;0;0;0;0;0;0;0;0;0;0;
ρt;60.28;60.28;60.28;60.28;59;59;59;59;57.87;57.87;57.87;57.87,...
...

```

Figure 1. Example of data format.

Proposing a standardized data format for ECs is crucial for several reasons. Firstly, ECs are a rapidly growing field that encompasses a wide range of stakeholders, including energy providers, consumers, regulators, and researchers. With such diverse participants, having a unified data format becomes essential for seamless communication, efficient collaboration, and accurate analysis.

Secondly, the interdisciplinary nature of EC management poses significant challenges. Integrating various aspects such as energy production, consumption patterns, environmental impacts, and socioeconomic factors requires the harmonization of data from multiple sources. A standardized format would facilitate data collection, aggregation, and comparison, enabling researchers and practitioners to gain deeper insights into the performance and dynamics of ECs.

Additionally, a common data format would enhance the accessibility and usability of EC-related information. By providing a user-friendly platform that aggregates case studies from around the world, stakeholders can easily access valuable data, benchmark performance, and identify best practices. This not only accelerates the development of

innovative solutions but also encourages the proliferation of knowledge and information sharing within the EC community.

Moreover, a standardized data format would pave the way for establishing benchmarks and reference points for EC management. By analyzing and comparing data across different communities, researchers and policymakers can identify successful strategies, evaluate the effectiveness of policies, and drive continuous improvement. These benchmarks would serve as valuable resources for developing new problem-solving techniques and enhancing the overall performance and sustainability of ECs.

Therefore, proposing a format for standardized data in renewable energy communities is a crucial step toward fostering collaboration, improving data management, and promoting innovation. By providing a unified platform and benchmarks, this approach can unlock the full potential of ECs, leading to more efficient and effective renewable energy systems on a global scale.

In addition, our vision extends to the future inclusion of this standardized format in widely used file formats such as JSON, as well as in any programming language that demonstrates user-friendly capabilities. By embracing multiple formats and languages, we aim to maximize accessibility and ease of use for stakeholders involved in ECs. This approach acknowledges the diverse backgrounds and preferences of users, enabling them to work with familiar tools and languages while adhering to a unified data format.

4. Conclusions

This paper presents a comprehensive literature-based analysis to identify the major input data for sizing ECs, classify them, and propose a data format template for sharing the needed information, to promote standardization, facilitate data sharing, and fast-forward ECs development. Environmental, social, and economical aspects have been taken into account, providing a comprehensive outlook on ECs that can be useful to several stakeholders, such as researchers and public authorities, to minimize the carbon footprint.

The proposed literature-based analysis highlights that various components covering electricity, thermal, and cooling needs are needed, whose parameterization requires information of different types and sizes, to be captured by data standards. In particular, the cardinality of those data has been extensively reviewed, and the results suggest that tabular-like formats can successfully capture the required needs. However, the format shall be sufficiently flexible to adapt to ECs with various numbers of members, technologies of energy production, types of storage and conversion, energy vectors, and market structures. A template for a numerical case study in Pisa, Italy is also proposed to suggest the suitability of the proposed data format for planning and operation studies. The proposed dataset employs a CSV-format, as an example, and it is largely populated with data derived from measurements.

These findings lay the groundwork for defining standards of data collection and data sharing for ECs and energy systems, which is of utmost importance to facilitate the widespread adoption of decentralized renewable sources. Future works may involve carrying out real case studies exploiting the collection and utilization of data in the presented format, as well as the definition of possible notable instances of data for algorithm benchmarking.

Author Contributions: Conceptualization, D.F. and D.T.; methodology, D.F., D.T., E.G. and E.S.; software, D.T., E.G.; validation, D.P.; formal analysis, D.T. and E.S.; investigation, D.T., E.G., I.M. and E.S.; resources, D.T., I.M. and E.S.; data curation, D.T. and E.G.; writing—original draft preparation, D.T., E.G. and E.S.; writing—review and editing, D.F., D.T., E.G. and D.P.; supervision, D.F., D.T. and D.P.; project administration, M.R., D.F. and D.T.; and funding acquisition, M.R. All authors have read and agreed to the published version of the manuscript.

Funding: The research has been conducted during and with the support of the Italian inter-university PhD course in Sustainable Development and Climate Change (<https://www.phd-sdc.it/>) and carried out in the framework of the project “AUTENS” (Sustainable Energy Autarky), funded by the University of Pisa, Italy (PRA 2020 programme).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Data are available on <https://github.com/dimitri-thomopoulos/DASH-EC>, accessed on 9 August 2023.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EC	Energy communities
REC	Renewable energy communities
RES	Renewable energy systems
PV	Photovoltaic
HP	Heat pump
COP	Coefficient of performance
ST	Solar thermal
TES	Thermal energy storage
CHP	Combined heat and power
CCHP	Combined cooling, heating, and power
CAPEX	Purchase cost

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