Towards data-driven energy communities: A review of open-source datasets, models and tools

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Towards data-driven energy communities: a review of open-source datasets, models and tools

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Abstract

Energy communities will play a central role in the sustainable energy transition by helping inform and engage end users to become more responsible consumers of energy. However, the true potential of energy communities can only be unlocked at scale. This scalability requires data-driven solutions that model not just the behaviours of building occupants but also of energy flexible resources in buildings and grid conditions in general. This understanding can then be utilized for a variety of downstream tasks such as reducing the cost and carbon intensity of energy, improving the stability of the electricity grid and allowing for greater proliferation of variable renewable energy sources such as wind and solar. However, in practice, collecting and cleaning the data necessary to realize these objectives forms a large part of such projects. This can be considerably accelerated by utilizing open source datasets from similar existing projects. Likewise, a number of open source tools exist that can help practitioners achieve state of the art performance in most tasks of practical interest with minor adaptations. This review provides an overview of these open-source datasets, models and tools, and the many ways they can be utilized in energy community projects.

Keywords: energy communities,, open-source, forecasting, optimal control

1. Introduction

Climate change concerns and accelerating digitization are causing arguably the largest shift in energy systems in the last decades [1], [2]. In many places, climate concerns have resulted in efforts to transition the energy system from a supply-driven system to a demand-centric one that facilitates an ever increasing proliferation of renewable energy sources (such as wind and solar) [3]. Digitization has been a vital technology enabling system operators

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better visibility to plan and operate the energy grid in light of the variability and intermittency introduced by renewable energy sources (RES). In addition to these top-down policy instruments and market innovations, bottom-up citizen initiatives (such as local energy communities) have also emerged as viable candidates that can help increase the proliferation of renewable energy technologies at a local level, while emphasising self-sufficiency, local determination, engagement and empowerment of citizens and energy users [4].

1.1. Local Energy Communities (LECs)

There is no standardized definition for energy communities, despite their long history. This has allowed many variants to emerge over the years, such as local energy communities (LECs), citizen energy communities, and market energy communities etc. However, some commonalities exist. Mainly depending on the scope of work and how the characteristics of community are defined, researchers and practitioners have defined it in numerous ways [5], [6], [7]. However, in most cases, energy communities are characterized by a strong emphasis on renewable energy resources and innovations in renewable technologies [[8], [9], [10]]; decentralized ownership through local stakeholders' involvement [[11], [12]]; and sharing of financial/social benefits for the local community [[13], [14], [15]]. In this paper, we will use LECs as an umbrella term to refer to all of these concepts.

A number of European countries (such as Sweden, Denmark and The Netherlands) were forerunners in developing local energy communities (LECs). The Tvindkraft Project[1] developed in Denmark in 1978 is one such early example of a local energy community. From there, the idea spread to other European countries including Germany and the United Kingdom, and beyond [16]. On the EU level, Recast Renewable Energy Directive (RED-II) focuses on stimulating the development of 'renewable energy communities' in all the Member States [17]. Likewise, the European Union 2030 energy and climate framework [18], UK energy and climate change strategy [19], and the Japan Strategic Energy Plan [20]) all include stipulations to support energy communities in one form or the other. Partly as a result of these policies, as of April 2020, the European Federation of Citizen Energy includes a network of 1500 European energy cooperatives and about 1 million citizens active in the energy transition [2]. In Germany alone, there are 869 energy cooperatives with 183,000 members [21]. Similarly, in the USA, the National Rural Electric Cooperative Association (NRECA) represents more than 900 citizen energy cooperatives. Some important LEC projects in Europe have been covered in [22], [16].

In practical terms, LECs have proven helpful in managing energy consumption and reducing emission levels, while engaging end users. LECs are also seen as a means of providing affordable access to (clean) energy to people in developing countries. The idea of community energy is suitable for tackling the socio-economic problems, which span more dimensions than simply access to energy. LECs, by virtue of promoting self-sufficiency, fits well especially in the rural areas of such developing countries where possibly the main energy grid does not exist yet [6]. These local communities vary in sizes and technologies depending

[1] https://www.tvindkraft.dk/en/
[2] https://www.rescoop.eu/

on the resources available. For example, use of community solar and micro-hydro plants is common in South and South East Asia because of abundance of water streams [23]. Similar projects in Afghanistan, Indonesia, Sri-Lanka and Nepal have also been successful [6]. There are many examples of LEC projects throughout the developing world [24]. Some of the most interesting practical use cases, in both developed and developing countries, are discussed in subsequent sections.

1.2. Digitization

A key enabling technology to operationalize energy communities in practice is increasing digitisation. The most critical component of this operationalization is the advanced metering infrastructure, which provides a way to record energy demand and generation values in real time, thereby paving the way for monitoring, user engagement, peer to peer trading concepts and downstream optimization [25]. This data-driven analysis, visualization and optimization requires sophisticated tools that can often be prohibitively expensive for bottom-up citizen initiatives. Furthermore, when not mandated by law, accessibility to these services also places the onus of data collection via metering on the energy community. This can likewise be a costly endeavor, especially before the benefits of such data collection are unclear at the onset.

An attractive alternative for analysing the data being generated by an energy community and perform optimization on demand and generation streams is made possible by large scale open-source software projects. Many of these projects are software tools meant to help analyze the vast amounts of data being recorded, while others focus on providing the infrastructure underlying the execution of the other tools. The motivation for software developers participating in these open source projects is usually multi-fold [26]. On the one hand, there are intrinsic rewards for participation, such as altruism and personal fulfilment. On the other, extrinsic rewards such as expected future returns also play a large role in contributing to open source projects. More recently, a number of large companies such as Google, Facebook and Microsoft have started open sourcing their internal tools (often focused on analysing data at different stages of a project's life) in an effort to more broadly involve the community in the development of software systems [27]. This gesture is also meant to be a way of returning to the community and helping accelerate advances to state of the art.

Replacing proprietary tools with open source ones can considerably lower the costs for an energy community. The optimal design and operation of energy communities can further benefit from already existing publicly available datasets collected in similar settings. This open sourcing of datasets is, in many cases, mandated by project funding bodies, which may require or request that data collected using public money should be made available for future scientific research. This includes the emphasis placed on open access and data management in Horizon 2020 projects by the European Commission [28]. Open access can also include free-of-charge provision to publications and/or research data arising from funded research projects (according to the conditions set forth in the grant agreement). In many cases, this agreement allows for an embargo period to allow the concerned parties to recover their costs, if any. Stringent data management plans, on the other hand, ensure that data generated in different projects continues to be available after the completion of a project. Towards this end, a host of services such as Zenodo have become popular with researchers in recent years [29]. Besides compliance with grant agreements, open sourcing datasets can also benefit companies, research organizations and society at large by helping advance state of the art as in the case of combating epidemics [30], or in addressing specific business related challenges, as with the netflix prize [31].

1.3. Challenges

Even though utilizing open source tools and datasets can considerably improve the economic viability of LECs, a number of challenges remain. For instance, it has been hypothesized that the energy sector has lagged behind in both specialized open source projects to analyse energy data and publicly available datasets of energy demand and production [32]. Some of the reasons for delayed adoption in the energy domain are large institutional inertia, privacy concerns and the slow pace of digitization. Legislation and regulation requiring metering of energy data has also hit roadblocks in many countries, with even the European Union showing a fractured landscape. Furthermore, the disparate nature of many different energy vectors (including electricity, gas, heat etc.) complicate efforts to measure demand and supply in a holistic manner. Finally, the data being recorded oftentimes leads to loss of privacy and can leave customers vulnerable to security exploits - which means data availability and privacy concerns go hand in hand [33].

Beyond these regulatory and market-driven challenges, a number of operational issues persist before LECs can become practically viable. Foremost amongst these is the fact that LECs rely on either direct user engagement or automation to elicit energy flexibility that can be used to improve energy usage or grid status in some way. However, in practice, both of these instruments can be quite limited in scope. For instance, automation-driven flexibility is limited only to devices which enable remote control (via edge, cloud or cloud-edge computations). In practice, there are only a few controllable loads in residential buildings such as heat pumps (used for space conditioning and hot water production), white goods, electric batteries and electric vehicles, as well as rooftop solar PV panels. Even though they are considered as solutions that can enable demand response and community energy, most of these energy flexible resources can create new (or exacerbate existing) stressors on the electric grid [34]. Furthermore, the instrumentation required to enable this automation can be quite expensive. Similar issues persist with direct user engagement: providing feedback to users can lead to information fatigue, especially when the financial rewards are low. Further, convincing users to install more energy efficient appliances can have a rebound effect on usage, implying that gains in efficiency do not always translate to an equivalent reduction in emissions [35].

Therefore, in the business as usual scenario, LECs face a number of operational hurdles (limited flexibility in the case of automation, user indifference in the case of engagement). Even in the best case scenario when these flexibility sources are available, the lack of availability of data and tools necessary to analyse the collected data can prove to be prohibitive stumbling blocks.

1.4. Contributions

This paper presents a detailed overview of the open source tools, datasets and models that LECs can employ to operationalize in practice. The information presented herein is also of interest to the wider community of architects, and building engineers and operators. By providing this information in a concise form, this paper will form a quick reference guide for practitioners and researchers alike. At the same time, by compiling the relevant resources in one place, the paper will also serve as a snapshot in time of the available tools and datasets for posterity's sake. Finally, even though the paper cannot directly influence the amount of energy flexibility available in an LEC, it will provide the tools (and data) necessary to estimate and leverage this flexibility in practice.

More concretely, we focus on LECs from the perspective of electrical energy demand and supply. In section 2, we highlight a number of the most interesting use cases that data has enabled for LECs. Section 3 provides a brief distinction between the terminology employed in this paper. Section 4 is a compilation of open-source datasets that can be leveraged in LECs, including demand side data in the built environment, generation data (focusing on renewable energy sources), as well as relevant markets and weather data. Section 5 discusses existing models which have been built using either human domain expertise or using collected data that could not be made available due to privacy concerns. These models can, in turn, be used to generate data that can then be used for further analysis in real world LECs. Related to these software models, section 6 provides a review of some of the most useful open source projects that can be utilized to gain insights from energy-related data in LECs. Section 7 provides a conclusion, as well as some future directions for research in and operationalization of LECs.

2. Data use cases in LECs

Data availability is critical for the successful operationalization of LECs, both during the design and the operational phase. During the design phase, it is necessary to estimate the optimal dimensioning of local energy flexible resources (EFRs) such as solar PV and battery-inverter systems. On the other hand, in the operational phase, it is necessary to operate these EFRs in a way that helps achieve community goals such as maximal self sufficiency (or self-consumption of local renewables) and minimal grid offtake.

For the case where a LEC is being designed from scratch, no prior data exists in many cases. Even in the case of operationalizing an existing LEC, data may be available but in a form that is not useful. Openly available datasets and tools to analyse them can reduce replication work, and even substantially accelerate development of new projects as they minimize the time and resources spent gathering and cleaning data [36].

In recent years, there has been a greater focus to overcome data-related challenges in order to achieve different objectives in LECs across the world. In this section, we briefly highlight some of the most important use cases that have been enabled by the use of openly available data and data analysis tools in LECs. In the subsequent sections, we will present the resources necessary to realize them in practice.

2.1. Optimally designing a LEC

Data-driven analytics and insights can help improve the design of components, appliances and buildings in a LEC. Practically, this is typically done to optimize the dimensions of storage and generation systems in the LEC. This optimization can only be carried out with some knowledge of the consumption patterns in the LEC, the grid constraints and the local weather conditions. Each of these factors considerably alters the optimal resource mix in the LEC. For instance, LECs in North-West European countries frequently need to over-dimension storage to bridge the diurnal supply-demand gap, and also consider long-term storage (e.g. in aquifers) to bridge the seasonal supply-demand gap. For regions with a smaller mismatch between supply and demand, this is often not required.

In a practical sense, data from existing projects can be used to refine future design and dimensioning of energy flexible resources in an iterative manner. These can then be used to maximize building thermal efficiency [37], [38], heat pump coefficient of performance [39], battery efficiency [40], and lighting efficiency. In practice, these interventions can lead to achieving the same objectives at a lower price point. On the other hand, practitioners designing a LEC (or the prosumers constituting the LEC) need to also consider geographical data and conditions to optimally choose the energy flexible resources that need to be installed. A frequently explored problem is the optimal dimensiononing of rooftop solar PV and local storage systems [41]. The objective of this optimization can again be manifold; and ranges from minimizing energy costs [42] and greenhouse gases [43] to maximizing the self-sufficiency of the building [44].

At this point, it is also pertinent to point out that system operators, on both transmission and distribution level, can use this information to plan grid expansion (or unit retirement) [45], [46]. Heat and transportation electrification as well as the rise of DERs will necessitate grid reinforcement investment discussions. These can be alleviated, to some extent, by focusing on the use of these technologies as means of flexibility provision - thereby fulfilling one of the key purposes of LECs.

Fig. of design optimization

2.2. Optimally operating a LEC

The actual operation of a LEC can be divided into multiple sub-components. These include the actual operation (i.e. tracking the energy flows) and the optimization of the energy flows (either through optimal control or user engagement).

2.2.1. Trading concepts and P2P energy markets

Peer-to-Peer (P2P) energy trading concepts enable energy from small-scale Distributed Energy Resources (DERs) in a LEC to be traded among local energy prosumers and consumers. Some preliminary results from LV grid-connected LECs show that P2P energy trading is able to improve the local balance of energy generation and consumption [47]. Moreover, the increased diversity of generation and load profiles of peers is able to further facilitate the balance. Such P2P energy trading is a special case of the broader class of LEC use cases, where prosumers located in a LEC can make use of DERs to maximize their self-consumption and avoid the consumption of (expensive or polluting) electricity from the main grid.

2.2.2. Optimization

Operational optimization makes direct use of data being collected on-site to achieve a variety of different objectives that fall under either demand reduction or demand response. Demand reduction typically refers to providing building occupants with the same level of comfort at a reduced energy expense [48]. Demand response, on the other hand, shifts energy demand from one time to another - typically by using an energy flexible resource such as an electrical battery or a heat pump etc. [49]. This is often to meet some pre-specified objective, such as peak shaving [50], valley filling [51], price arbitrage [52], load following [53], self-consumption [54], frequency or voltage regulation [55], [56] or a combination of them. In the context of LECs, data can be used to learn models for the demand side, price signals and the local supply which are then used as inputs to an optimization algorithm to reach the aforementioned objectives [57]. [58].

Fig. of operational optimization

In addition to automated control, it is also possible to affect the energy balances in a grid by engaging users to reduce their footprint [59]. This has been demonstrated in a number of studies, and typically takes the form of providing comparisons to neighbors and other similar households [60]. Another example of such an undertaking is the community challenges in LES, as explained above. The results allows individuals to actively engage and feel involved in the local energy community as well as changing their behaviors to achieve community targets. For example, interventions tested across 300 houses in Groningen (Netherlands) demonstrated a net energy reduction of 8.5% [61]. Opower has likewise built a business model on such interventions [62].

3. The distinction between datasets, models and tools

Before proceeding with a review of different components of a data-driven energy community, it is important to make the distinction between datasets, models and tools explicit.

1. A **dataset** refers to the raw data that has been made available for further analysis. This is often in the form of a time series, and can be complemented by additional metadata. An example of a dataset can be the actual electricity demand of a building, while the metadata can provide information about demographics of building occupants and the geographical location of the building etc.
2. A **model**, on the other hand, distills the information from a dataset (that may or may not be made available in addition to the model) into a directly usable or interpretable form. The model is therefore more restrictive than the broader dataset, and can be used to preserve user privacy, for instance. However, it is also possible to develop models from first principles (rather than using observation data). Such models are a valuable source of information in cases where real world data is not available or collecting it can be expensive. These models are also useful for cases where the physics of the process is well understood.

Variants_model_data_tools.png

Figure 1: The distinction between data, models and the use case employing the tools; (a) model-free methods directly utilize data to optimize some metric of interest e.g. model-free control of energy flexible resources; (b, c, and d) model-based methods depending on data, domain knowledge or both to construct a model that is used for subsequent analysis; (e) privacy-preserving use cases where only a model trained on user data is utilized

3. The **tools** considered in this paper refer to existing, open-source software projects that can be used, either directly or indirectly, to provide services in the energy sector. This includes both tools developed specifically for the energy domain as well as general purpose tools that have been outsourced by practitioners in other domains. As there are a wide array of such tools available, we have made an effort to include only the tools that can be useful directly for LECs, or for practitioners and researchers in the field.

The distinctions between these three is made clear in Figure 1.

4. Datasets

This section summarizes a number of publicly available datasets along a number of important dimensions, both on the demand and the supply side. In addition to these, other exogenous factors that may influence the functioning of an energy community, such as ambient conditions as well as real-time prices and carbon intensity of electricity is presented. Where readily available, data from developing countries is highlighted as this data is much more sparse, and electrification in these countries represents the bulk of future demand growth.

4.1. Demand side data

The energy demand in a LEC drives all downstream business cases. Therefore, getting greater visibility on the demand side is arguably the most important advantage of openly available datasets for practitioners in the field. LECs can help address the increasing supply-demand imbalances by leveraging the demand side flexibility in buildings, either through automation or user engagement.

It is possible to make two distinctions for demand side data:

1. The scale of the building itself, i.e. whether we are considering a residential or commercial building. Typically, commercial buildings offer substantially more flexibility than residential buildings, which makes intuitive sense. However, LECs typically constitute residential buildings, with a focus on energy prosumers. Increasingly, however, the definition of LECs is being expanded to include commercial buildings in neighborhoods.
2. It is also possible to distinguish datasets according to the resolution of collected data. More specifically, a number of recent studies have focused on disaggregation of electrical loads from the observed load profile - also referred to as non-intrusive load monitoring. The key factor differentiating these datasets is their high sampling frequency and sub-metering of individual loads.

This section is organized as follows. We begin by providing a review of residential energy demand, both on an aggregated and disaggregated level. We follow this by briefly discussing commercial building loads that could also be considered useful for future LEC projects.

4.1.1. Residential building energy demand

Researchers and practitioners have made available a large number of datasets for residential energy demand. These datasets differ according to the geography of the buildings, but also in the amount of households they make available. Furthermore, some datasets only provide electrical consumption, while others also provide metadata (e.g. to describe household characteristics) or other sensor data such as water and gas consumption. As mentioned before, the temporal resolution of sensing is also very different. We begin with datasets which are sampled at a high enough temporal resolution to enable non-intrusive load monitoring:

1. The EMBED dataset [63] includes labeled electricity disaggregation dataset containing plug load consumption data for different appliances in 3 US apartment units in California. The plug load data is collected at 1-2 Hz sampling frequency, while the current and voltage are sampled at 12 kHz. Data collection duration is 14-27 days
2. The REDD dataset (Reference Energy Disaggregation Dataset) [64], likewise, consists of whole-home and circuit/device specific electricity consumption for 6 US housing units over 3-19 days. The dataset provides power and voltage information recorded at a high frequency (15kHz), up to 24 individual circuits in the home, each labeled with its category of appliance or appliances, recorded at 0.5 Hz, and up to 20 plug-level monitors in the home, recorded at 1 Hz.

3. The BLUED energy disaggregation dataset [65] includes current and voltage measurements from one US single-family residence, sampled at 12 kHz for 8 days. The dataset includes time-stamped and labeled state transitions of each appliance in the home during this time.
4. The PLAID (Plug-Level Appliance Identification Dataset) dataset [66] is a public, crowd-sourced dataset of high-resolution electrical appliance measurements for load identification research, consisting of short voltage and current measurements (in the order of a few seconds) for different residential appliances. PLAID currently contains measurements for more than 200 different appliance instances, representing 11 appliance classes, and totaling more than a thousand records.
5. The ADRES concept [67] dataset provides data on power consumption and voltage profiles from 30 Austrian households. The measurements were taken for a week in the winter (between September to December 2009) and one in the summer (between May to October 2010) with a resolution of 1 second. However, the dataset does not include detailed appliance level data.
6. The REFIT dataset [68] includes raw electrical consumption data in Watts for 20 households at aggregate and appliance level, timestamped and sampled at 8 second intervals over a period of two years.
7. UK-DALE [69] is a domestic appliance level electricity dataset from five households in the UK. In each house, both the whole-house mains power demand every six seconds as well as power demand from individual appliances are recorded every six seconds. In three of the five houses (houses 1, 2 and 5) the whole-house voltage and current is also recorded at 16 kHz. Data from household 1 is now available for well over 4 years and can facilitate long term analysis of seasonalities and trends.
8. The DRED (Dutch residential energy dataset) [70] dataset includes electricity data (aggregated energy consumption and appliance level energy consumption), ambient information (room-level indoor temperature, outdoor temperature, environmental parameters), occupancy information and household information.

In addition to the datasets providing high temporal resolution, a number of other datasets also exist. These typically cover a greater number of buildings and data collection typically lasts a longer duration than a few days or weeks, due to the relative simplicity of gathering, transmitting and storing data.

1. Dataport [71] is a large scale dataset which contains one-minute appliance-level customer electricity demand from around 1400 houses and apartments for multiple years.
2. Smart* data set [72] is another large scale dataset which makes available electricity consumption data from over 400 anonymized homes besides detailed meta-data on a number of apartments and homes. The closely related NIOM dataset combines electricity consumption with occupancy patterns in the building for 3 weeks of minute level data on consumption and occupancy.
3. AMPDs [73] contains electricity, water, and natural gas measurements at one minute intervals for two years. There are a total of 21 power meters, 2 water meters (with

additional appliance usage annotations), and 2 natural gas meters. Weather data from Environment Canada's YVR weather station is also included in the dataset.

4. The PRECON dataset [74] has been collected in Pakistan over a period of one year, of electricity consumption patterns for 42 residential properties having varied demographics. Data is collected for the whole house consumption and from high powered devices as well as from major areas of the building. Additional meta-data such as demographics information etc. is also included in the dataset.

4.1.2. Commercial buildings

Commercial buildings can take on a number of different forms. Increasingly, such buildings can also become part of an energy community, because of the presence of energy flexible resources such as solar PV panels, batteries and electric heating or vehicle charge poles. This section includes an overview of public datasets detailing energy demand in commercial buildings.

1. The BLOND dataset [75] offers continuous energy measurements of a typical office environment at high sampling rates with common appliances and load profiles. The dataset contains 53 appliances (17 classes) in a 3-phase power grid over 213 days of uninterrupted measurements sampled at 50 kHz (aggregate) and 6.4kHz (individual appliances).
2. The I-BLEND dataset [76] includes 52 months of electrical energy data at a one-minute sampling rate from commercial and residential buildings of an academic institute campus in India. Additionally occupancy datasets at a 10-minute sampling rate for each of the campus buildings are also provided.
3. The COMBED (commercial building energy data set) dataset [77] contains energy data for one month from IITD's academic building sampled at more than once a minute.
4. The IEEE Power and Energy Society (PES) has an additional repository of datasets from commercial buildings[3]. These include sub-metered measurements in different offices on the second scale. However, the data collection period is typically on the order of a few weeks to months.
5. The ASHRAE great energy predictor III challenge dataset on Kaggle includes three years of hourly meter readings from over one thousand buildings at several different sites (https://www.kaggle.com/c/ashrae-energy-prediction). This competition is a follow-up to earlier competitions also conducted by ASHRAE [78].
6. The Building Data Genome Project [79] compiles an open data set from 507 non-residential buildings for one year, including hourly whole building electrical meter data. The dataset also contains meta data such as or area, weather, and primary use type.

[3]http://sites.ieee.org/pes-iss/data-sets/

4.1.3. Electric vehicle data

In addition to energy demand from classical loads in the buildings (e.g. illumination, ventilatione etc.), electrification of transport will make charging electric vehicles a significant load as well. This is also in line with European regulation which mandates minimum EV charging pole requirements for commercial buildings. However, openly available data for EV charging remains sparse. An exception is the dataset made available by ElaadNL[4]. This dataset contains aggregated data from public, private, and workplace charging stations.

4.2. Climate related data

Local weather conditions are among the biggest drivers behind both energy demand and energy flexibility in a LEC at any given time [80]. As such, it is important to know these conditions during both the design and operation phase. Having an accurate forecast for ambient conditions ensures an accurate picture of future energy demand and production. Historical data, on the other hand, allows practitioners to build the regression models that can model this relationship. The prosumer response in light of climatic and weather conditions therefore represents an opportunity for LECs to capitalize. In this section, we briefly explore climate related datasets. The section is divided into three subsections. First, we discuss general weather conditions, second we present an overview of datasets dealing with electricity production potential from renewable energy sources, and finally we address the long term effect of climate change on ambient conditions.

4.2.1. General weather conditions

A number of online services provide access to weather data, both historically and in (near-)real time. Many of these provide this data for free - usually to a certain number of API calls per day or month etc. These services include, besides many others, OpenWeatherMap, Darksky (now acquired by Apple Inc.), Accuweather and Weatherbit. Most of these services have a free tier with limited access, and provide both historical data and future (short-term) forecasts for ambient conditions such as temperature, humidity, precipitation and cloud cover. The time resolution is typically on the order of minutes to hours, and the forecast horizons vary between a few days to weeks. Increasingly, these services are incorporating environmental quality variables such as CO2 concentration etc. into their offerings.

These services are useful for micro-level analysis, i.e. when the specific location of the LEC is known. For cases where a regional analysis needs to be performed, alternatives based on global climate simulations or satellite data might be preferable. These usually offer data at a coarser resolution, and include:

1. ECMWF CAMS real time provides ambient conditions data and forecasts for temperature, precipitation, snowfall and air quality metrics, besides many others. The data coverage on global scale is quite extensive. The forecasts from the service are freely available on a multiple day horizon, and they are updated four times every day (at 00:00, 06:00, 12:00 and 18:00)[5].

[4] https://www.elaad.nl/news/elaadnl-shares-new-data-sets-demonstrating-the-rise-of-evs-and-usage-of-charging-stations/

[5] https://apps.ecmwf.int/datasets/data/cams-nrealtime/levtype=sfc/

2. ECMWF ERA5: provides irradiation data through a separate reanalysis product, which spans back decades to also optimally combine historical data with future forecasts. The grid in this case is 31x31 km, and the data is only available on an hourly scale. The forecast values can be especially inaccurate in coastal areas, mountains, cloudy regions and anywhere with lots of shading.[6].
3. SARAH 2 is another free-to-use dataset with a higher spatial resolution, which is also available on 30 minute intervals. This dataset can also be found online[7].

4.2.2. Climate change

In addition to providing historic data or short-term forecasts for the future, a number of openly available data sources also provide long-term projections in light of climate change. These different climate models usually rely on different pathways for future energy systems and the global economy [81], [82]. For instance, a number of energy pathways exist to achieve the Paris climate goal of limiting temperature change below 2°C, however they invariably disagree on the actual measures required to make this happen (as well as the timing of these steps). This means that there is a lot of uncertainty about the emissions reductions at any given point in the future. This is exacerbated due to uncertain inertial and tipping point effects in the global climate. Consequently, climate models are inherently noisy as they rely on changes not just to global climate dynamics but also on factors such as the global economy and energy systems. Nevertheless, these scenarios are useful while designing and operating LECs. Some of these resources include:

1. The WorldClim 2 dataset provides spatially interpolated monthly climate data for global land areas at a spatial resolution of approximately 1 km2. The data fields include temperature (minimum, maximum and average), precipitation, solar radiation, vapour pressure and wind speed [83]. The forecast monthly values are averages over 20 year periods (2021-2040, 241-2060, 2061-2080, 2081-2100). Both historical and future data are available online, as downscaled CMIP6 future climate projections[8].
2. The World Bank provides similar data fields in a more accessible fashion through their climate change knowledge portal[9]. With this tool, it is straightforward to export historical and future projections for temperature (minimum, maximum and average), precipitation, heating and cooling degree days etc. It is possible to access this information by longitude/latitude or country name. These projections are based on CMIP5 simulations for the global climate, the precursor to CMIP6 simulations used by WorldClim above.

4.2.3. Generation potential of renewables

On-ground data for electricity production with renewable energy sources is openly available for large parts of the globe. This can help LEC planners with optimally dimensioning

[6] https://confluence.ecmwf.int/plugins/servlet/mobile?contentId=129135000content/view/129135000
[7] https://wui.cmsaf.eu/safira/action/viewICDRDetails?acronym=SARAH$_V$002$_ICDR$
[8] https://www.worldclim.org
[9] https://climateknowledgeportal.worldbank.org/download-data

their distributed energy resources (DERs). Some data providers also include forecasts in the near-term. However, these are generally on a larger aggregation level than a single neighborhood; the data can however be scaled down to local regions. Note that in this section, we only consider actual data and forecasts for electricity generated by renewables; in subsequent sections, we will also present theoretical generation potential under ideal conditions. The resources mentioned earlier in this section can also help estimating the potential, but in this section we focus on actual data from renewable generation. Some of these resources include:

1. ENTSO-E, the European Network of Transmission System Operators for Electricity, provides a forecast of renewable energy sources such as wind and solar power generation (MW) per bidding zone, per each market time unit for the following day. This information is provided for all bidding zones in Member States with greater than 1% feed-in of wind or solar power generation. More specifically, ENTSO-E provides (1) the current forecast, (2) the day ahead forecast at 18.00 (on the previous day) and (3) the intraday forecast at 8.00 (on the same day).
2. Some transmission system operators, such as Elia in Belgium, also provide multi-scale (hour-ahead, day-ahead, week-ahead etc.) forecasts for solar PV electricity production, disaggregated regionally which can provide more granular information to operators of LECs.
3. EIA, the US Energy Information Administration, provides hourly electric grid data by eight different generation sources (including solar PV, wind and hydro).

5. Models

Models provide the option to generate data for specific scenarios and assets when it is not possible to obtain real data, due to technical or economic constraints. Especially for LECs, this can be quite useful for cases where no similar projects have been executed before (or the data generated in them is not publicly available). Models can also be helpful when defining a benchmark for comparing different techniques or scenarios. In this section we describe a number of models following the same classification as before: demand-side, generation-side. Additionally, in this section, we also consider resources for power systems and storage.

5.1. Synthetic demand side data

In this section, we focus on models that are available to simulate energy-related behaviour of buildings (and building occupants). These models usually rely either on top-down models, which are typically based on behavioural models of user demand, or on bottom-up approaches, which emphasize individual appliance usage and are built using either diary data or, increasingly, sub-metered or disaggregated appliance loads. These models try to generalize using statistical data from end-users behaviours and interaction with their devices. The following are some models that can be used to generate load profiles for residential and commercial building users:

1. Load Profile Generator (LPG) generates artificial load profiles for residential energy consumption by simulating the people in one household, thereby obtaining their load curves [84, 85]. The model, based on German households, uses insights from psychology and can generate data for large populations of up to 1000 households.
2. The Artificial Load Profile Generator (ALPG) [86, 87] is a model that uses high level demographic statistics as an input to build a bottom-up model and generate electricity load profiles. This is particularly interesting for LECs as the model characterizes devices as uncontrollable, curtailale, time-shiftable, buffer time-shiftable and buffer.
3. The House Load Electricity [88, 89] is an application programmed in MATLAB that generates synthetic electricity load profiles based on consumer loads. The application comes with a Graphical User Interface (GUI) where the end-user can chose the model parameters, as well as change the time resolution and time periods generated.
4. Office Load MATLAB Application generates synthetic load profiles, but in this case for office buildings [90, 91]. As in the previous application, the user can specify the parameters in a MATLAB based GUI, representative for Northen Europe. The model is based on a bottom-up approach, collecting both the behavior of the office workers as well as the appliances installed in the specified office. Energy use of heating and air conditioning systems is taken into consideration.

5.2. Generation potential of renewables

In addition to the data sources mentioned in the previous section, there are a number of models available to simulate the behavior of DERs. This can be especially important when it is not feasible to get real data from already installed assets. In this section, we focus on solar PV panels. The next section completes the DER picture with battery models.

1. The Sandia Labs PV Performance model Program (PVPMC), developed by Sandia National Laboratories, provides a set of models covering from geological position, the orientation and specs of the PV panel as well as the converter. Parameters such as the sun position, irradiance and insolation, weather observations, array orientation, shading, soiling and reflection losses, DC module specifications, inverter technical characteristics, can be specified by the end-user. The first models were provided under MATLAB libraries [92], developing later the Python version described below.
2. The pvlib-python [93] offers several functions and classes for simulating the operation of PV energy systems. It is an open-source library that provides the models for these systems, based on the MATLAB toolbox, created by Sandia National Laboratories. It aims to provide the end-user with reliable, open and benchmark photovoltaic models. These models can be used to develop PV power forecasting tools, as well as evaluating different configurations of PV systems [94].
3. The NREL's PVWatts [95], developed by the National Renewable Energy Laboratory, provides a browser-based PV system model that estimates the electricity output and also the economic costs of grid-connected PV energy systems. The user can introduce the location of the PV panels as well as the PV system technical characteristics and the electricity-related market data.

4. Renewables.ninja is a web-based system that contains a PV energy system model to estimate the electricity power output of the system for any location (either input as country or a latitude-longitude combination) [96]. It also contains ready-made datasets by each country. In the case of PV energy systems, the user can add the technical specifications of the system, such as tilt, azimuth or capacity. Renewables.ninja is a GUI of the python model developed in [97]

5.3. Storage models

Energy storage systems (ESS) are among the most effective flexibility sources and can enable greater proliferation of renewables by unlocking self-consumption. This section focuses exclusively on electric storage. In the case of batteries, a general lack of real world observation data and the increasing number of projects integrating batteries has pushed the community to create and share their models, playing a key role in helping the integration of ESS in LECs. Some of these models include:

1. QuESt - Optimizing Energy Storage is a python-based application that contains energy storage models for simulation and analysis purposes [98, 99]. Furthermore, the application includes a data acquisition option that allows import of market data, transmission system data, load profiles and PV power profiles to calculate the profitability of the ESS.
2. OSESMO provides a battery model (for Lithium-ion and flow batteries) and calculates the optimal charge-discharge strategy in 15-minute time periods by means of a linear programming optimisation technique, in order to minimize the end-user monthly bill [100]. However, this tool does not provide load forecast; in fact perfect knowledge of historical data is considered.
3. The EnergyBoost is a learning-based control of Home Batteries that models a Lithium-ion battery for households, connected together with a PV energy system [101]. This physical model is then used to formulate the control of the battery charge and discharge operation by considering it an optimal control problem.
4. While EV battery models are more difficult to find than their fixed battery counterparts, Geotab has recently open-sourced a detailed EV battery degradation model over time[10]. This model allows users to visualize battery degradation over time for a number of different makes and models of EVs.

5.4. Other models of interest

In addition to the demand, storage and generation (via renewables), there are also a number of other models that can be utilized in the operation of LECs. An example is the System Advisory Model (SAM) created by NREL [102], which provides end-to-end decision making support for micro-grids and LECs. SAM incorporates different models (e.g. of renewable energy systems such as PV energy systems, Energy Storage Systems, concentrating solar power, wind power turbines, biomass combustion and solar water heating). It can

[10]https://storage.googleapis.com/geotab-sandbox/ev-battery-degradation/index.html

therefore be used to obtain data for the entire community considering different renewable and flexible assets installed [103].

In addition to these models, models for power systems can also be critical to better understanding the practical feasibility of LECs. There are a number of such models available, even though actual data remains sparse. These include the PowerGenome project [104], the Open Energy Modeling Framework (OEMOF) [105], the multi-vector simulator [106], and the renpassGIS [107].

6. Tools

As mentioned previously, a number of openly available tools exist to enable practitioners to analyze and draw insights from the datasets and models discussed above. These can be divided into general purpose tools that can be adapted to address issues in the energy domain, and tools which have been created specifically to address issues in the energy domain. This section provides a non-exhaustive overview of some of the most promising and widely utilized tools. It is worthwhile to remember that the section on models has some overlap with the tools, especially because researchers frequently couple models with additional tooling to support decision making etc.

6.1. General purpose tools

A wide variety of general purpose open-source data analytics frameworks have been developed over the past few years, which can also be utilized in the energy domain. In this section, we review some of the most commonly used tools that are available in Python, arguably the most popular data science language at the moment. Similar packages typically exist in R, Matlab and other programming languages; as such the idea in this and subsequent sections is only to use real-world tools for illustrating ways in which data analytics can be employed in practice. The applications in this section broadly mirror the same use cases as the ones highlighted earlier in this review.

6.1.1. Data wrangling and visualization

The first step in any data-driven project is to acquire relevant data. We have highlighted numerous data sources as well as models that can be used to generate such data in the previous sections. Once this data has been acquired, the first step in any such project is exploratory data analysis. This includes both summarization of key metrics (which can be achieved through libraries such as Pandas), and visualizaiton of key trends. Data-visualization can especially help in the process of better understanding the data, inferring key patterns and also some early decision-making.

Matplotlib is arguably the most well-known python library for creating static visualizations [108]. Although it started emulating the MATLAB aesthetics and commands, now it relies on numpy and other Pythonic libraries for creating data visualizations. One of the main advantages of matplotlib is the easy customization of the plots and figures. Seaborn [109] is another visualization library based on matplotlib and thus has the same philosophy of matplotlib. However, besides its ease of use, its default themes also appear generally more visually appealing and are suitable for reports and presentations.

Interactive data visualization and dashboards are gaining in popularity due to their ease of use. These can also enable easier and seamless user engagement, through thoughtfully crafted dashboards. Dash Plotly [110] is an open source python library which allows creation of highly customizable and interactive web-based dashboards from inside python programming language. Two open-source alternatives to create custom interactive dashboards include Panel [111] and Streamlit [112]. These go one step further, and allow the creation of web-apps and interactive plots in a very straight-forward manner, specifically for data science and machine learning projects.

6.1.2. Modelling and forecasting

Forecasting demand and generation using data-driven (or physical) models is arguably one of the core activities in a LEC. It enables energy trading, user engagement, anomaly detection and downstream optimization processes such as self-consumption etc. This can be done using either time series analysis tools, or with machine learning algorithms.

1. Time series analysis and forecasting is enabled by a number of foundational Python libraries such as Statsmodels, Scipy and Prophet. Statsmodels provides support for tools such as correlation and autocorrelation analysis of time series data (that can be useful for ARMA analysis), as well as running statistical tests. Scipy complements this functionality by providing support for general signal processing algorithms. Prophet, an open source tool from Facebook, allows for forecasting at scale by combining elements from classical time series analysis with automatic search strategies which allow better forecasts.
2. As opposed to time series analysis which typically decomposes a time series into its constituent components (or frequencies), machine learning tools can have broader applicability. The most common use case of forecasting energy demand, generation and prices can be done through regression analysis using these algorithms. This mapping can be either linear or nonlinear, and many libraries exist for this purpose. In Python, Scikit-learn is arguably the most comprehensive library which enables this functionality with a wide variety of models including linear models, support vector regression, tree-based methods (random forests and gradient boosting etc.) as well as Gaussian processes. More recently, a number of deep learning libraries such as Tensorflow and PyTorch have also come to the fore, enabling practitioners and researchers to train (deep) neural networks using their data (or making use of pre-trained neural networks). Other use cases include classification problems (e.g. disaggregation to identify individual devices), which typically use the same libraries as the ones for regression. Another use case is clustering, which is used to split similar members of a population into distinct sets (e.g. to group together buildings with similar energy demand). As before, clustering can also be done with the same libraries, even though specialized variants exist as well. Finally, it is sometimes useful to reduce the dimensionality of input data to facilitate visualization or learning; this is also enabled in Python with the same libraries.

6.1.3. Design and operational optimization

As opposed to time series analysis and machine learning methods for modelling and forecasting energy loads, design and operational optimization refers to actually utilizing this information to affect real world change. Optimization, regardless of whether it is for operational or design phase, can be carried out in practice using a wide variety of tools, as presented below.

1. *Convex optimization.* Many problems that need to be solved for LECs are convex (or can be convexified). An example of such problems is cost arbitrage. There are several tools for working with convex optimization in python, including Pyomo, PuLP and CVXPY:
   (a) Pyomo is a Python-based, open-source optimization modeling language [113, 114], which covers the formulation, solving and analysing steps of the optimization process. It allows both specific and symbolic problem definition, and support from linear to stochastic programming, covering quadratic, non-linear, both mixed-integer linear and not linear programming, and more. Furthermore, pyomo provides generic solvers for stochastic programming by means of the PySP package. Pyomo allows the usage of the most know solvers like GLPK, CPLEX, Gurobi, IPOPT, and others.
   (b) It is also possible to call solvers such as Gurobi directly from within Python by installing the module called gurobipy, which transforms it to a python-based modeling language for convex optimization [115]. Gurobipy allows the resolution of LP, QP and MIP (MILP, MIQP, and MIQCP) problems.
   (c) PuLP is a python library that allows the modeling of Linear Problems (LP) [116], which can call an external solver from a pre-specified portfolio like GLPK, COIN CLP/CBC, CPLEX and GUROBI for solving LP models.
   (d) CVXPY is a python modeling language specifically designed for convex optimization problems [117, 118]. One of the main advantages of this library is that it allows the user to formulate the problem by writing it in a natural way, instead of the problem formulation sometimes required by solvers. This library also supports quasiconvex programming (DQCP), and makes use of several solvers such as CVXOPT, GLPK, GUROBI, XPRESS, COIN CLP/CBC, CPLEX and NAG.
2. *Nonconvex optimization.* As opposed to convex optimization, it is also possible to carry out nonconvex optimization in Python. This can especially come in handy when the system model, the optimization objective function and the constraints are non-convex. In this case, derivative-free optimization tools such as DEAP [119] and Nevergrad [120] can be especially useful to obtain an approximately optimal solution. However, while this is an extremely versatile class of tools, in general if a problem can be solved using convex methods, those techniques should be utilized.
3. *Reinforcement learning.* Over the past few years, variants of reinforcement learning have emerged as feasible optimisation strategies for the energy domain, especially in settings where a model for the environment is not available. A number of libraries facilitate reinforcement learning. However as most of these are beign actively developed,

new libraries are coming up quite frequently. Some of the more notable libraries in this space include the OpenAI Gym [121], which allows researchers and practitioners alike to experiment with existing environments and benchmark different reinforcement learning algorithms. On the other hand, libraries like ChainerRL [122], KerasRL [123] and TensorForce [124] provide off-the-shelf implementations of a number of standard reinforcement learning algorithms.

4. *Bayesian optimization.* In situations where evaluating the objective function is computationally or physically expensive, (for instance in real world trials involving human users), it can be worthwhile to explore Bayesian optimization [125]. The general idea behind these algorithms is to first learn a surrogate function, often using Gaussian Processes, which allows them to intelligently sample the next solution. A practical example of such a tool in Python is Hyperopt [126].

6.1.4. Tracking tools

Previously, we have already highlighted tools to make dashboards to quickly present and analyse results. However, a relative newcomer that can automate the tracking of energy flows in a LEC is blockchain (or distributed ledger technology). Blockchain technology has found accelerating adoption in LECs and peer-to-peer energy trading concepts. Such a blockchain can be implemented in the definition of smart contracts, enhancing the deployment of peer-to-peer markets and therefore ensuring the traceability of the energy that is being produced and consumed within the community. To start with, arguably the most simple tool for Blockchain definition is hashlib, a python library [127]. This is done by first defining a block, also known as a hashing function that can be chosen in the same library (SHA512, SHA256, etc.). Afterwards, one can create a chain of blocks, connecting the previously created hashed blocks, and so generating the so-called blockchain.

6.2. Energy specific tools

While the tools presented above are applicable to multiple domains including energy, there are a number of open source tools that have been specifically developed for energy related problems. In this section, we briefly consider such tools and their utility to LECs. These tools mainly take the form of libraries for simulating either the built environment that form the basis for a LEC, or power systems that govern the flows of electricity.

6.2.1. Building systems simulation

Energy communities are based on the principle of being able to manage the DERs located within the community, to for instance minimize the grid-offtake of electricity, while promoting local self-consumption. In that sense, the possibility to simulate the performance and operation of building system can assist in the definition of resources to locate in a local energy community or to change the operation schemes and activities in it. In the previous sections we have presented datasets for energy demand and models that can be used to simulate these datasets. However, there are alternatives that take a more holistic approach, i.e. they are not limited to just generating demand data for the built environment, but also integrate the control element. An example is City Learn, an OpenAI Gym[11] environment, which aims to implement a multi-agent reinforcement learning for buildings, coordinating their energy consumption and production and demand-response activities [128]. This tool allows the implementation of different controllers to reshape load profiles, by controlling the operation of flexible resources such as domestic water boilers, electric heaters, PV panels, and space cooling.

6.2.2. Power systems simulation

Pandapower [129] is a general-purpose python-based power system analysis tool with the aim to perform power flow based on Newton-Raphson solver analysis. It also lets the user run basic AC/DC optimal power flow calculations of electrical grids. These can be used to maximize the utility of the LECs as described earlier. Pandapower is based on the now deprecated Pypower and a well-known MATLAB Tool for power system analysis, MATPOWER [130]. Pandapower library relies on the pandas library in Python for a better handling of data inputs and outputs, considering several types of inputs and outputs files. Another (non-Pythonic) open-source alternative for simulating electric power systems is OpenDSS [131]. OpenDSS models and simulates distribution networks as stand-alone executable programs, and can be used for planning a LEC and operating the flexibility resources contained in it.

7. Conclusions

In this paper, we have focused on local energy communities, and provided a detailed overview of publicly available datasets, tools and models that can be used to optimize their design and operation. Even though the energy domain has, in general, lagged behind other sectors when it comes to digitization, we have gathered here a multitude of resources in this review. These include openly available datasets that include the energy demand and generation (via renewable energy sources). These are complemented by models that can generate these datasets in more general settings. Where one or the other should be used, depends on the use case. A general rule of thumb is to use actual dataset if it is similar enough to the current use case. Models excel, however, when the design must use projections for the future. This is especially important for designing LECs, while remaining cognizant to the effects of climate change. Finally, the tools we highlighted in this paper include both general purpose data science related frameworks which can allow data visualization and modelling as well as optimization and tracking of energy flows.

More concretely, the resources presented in this paper can be utilized by LECs in a number of different ways to improve their performance. Here, we provide some brief guidelines:

1. **Aspiring LECs** often need to make assumptions to dimension the energy resources (e.g. battery-inverter sizing, solar PV dimensions etc.). The results of this analysis

[11]OpenAI Gym is a general purpose toolkit for developing and comparing reinforcement learning algorithms

can be considerably improved by making use of real-world data from similar projects, thereby improving the overall profitability of such systems. Likewise, such aspiring LECs can make extensive use of the frameworks and tools presented in this paper to optimize for their objectives, e.g. minimize grid-offtake or maximize self-consumption etc. This optimization is both time- and space-dependent, as both of these considerations (i.e. evolving local regulations) affect the profitability of such projects.

2. **Existing LECs** can primarily make use of the tools presented in this paper. For instance, the data visualization and modelling tools can help with engaging users and prosumers in LECs. On the other hand, the optimization algorithms and frameworks presented in this paper can be used to both optimally dimension the energy flexible resources (e.g. DERs, heat pumps etc.) and also to operate them in a way that it minimizes grid-offtake and maximizes self-consumption. Finally, the grid models and frameworks (e.g. OpenDSS and Pandapower) can be used by advanced practitioners to ensure that the energy flexible resources in the LEC can also help keep distribution grid operation stable (e.g. minimizing voltage and congestion issues etc.).

In gathering these resources, we have also unearthed some obvious shortcomings. These include a general lack of openly available data for electric vehicles. This extends beyond the energy demand, and encompasses mobility patterns and the long-term longevity of EV batteries, especially if they are used with fast chargers or in vehicle-to-grid mechanisms. Likewise, detailed data from space conditioning (heating, cooling, ventilation) and hot water production is quite limited, when compared with electricity demand data. Even in cases where the energy demand for space conditioning is sub-metered, it is not often that detailed temperature values are recorded inside the medium of interest (e.g. building and/or hot water vessel). Future works to address these issues will greatly assist in not just the design and operation of LECs, but the broader field of smart grids as a whole.

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