BS 2021 1-3 SEPT BRUGES

INTERNATIONAL BUILDING PERFORMANCE SIMULATION ASSOCIATION

Open and Reproducible Use Cases for Energy (ORUCE) methodology in systems design and operation: a dwelling photovoltaic self-consumption example

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Abstract

Historical energy system modelling as well as the current mainstream approaches are closed and proprietary. Yet, open energy modelling can be of particular interest in the building simulation community. This article presents the Open and Reproducible Use Cases for Energy (ORUCE) methodology, thought as a transferable workflow to make open energy modelling principles and advantages accessible. After underlining open energy modelling importance and best practices, the ORUCE methodology is presented for the first time, and applied for the energy design and operation of a dwelling photovoltaic self-consumption system. Finally, the quantitative results of the application as well as the qualitative results of the methodology are discussed.

Key Innovations

- ORUCE methodology: an easy to apply workflow for district scale open energy modelling whatever the model or framework, underlining the importance of use cases for open knowledge capitalisation.
- A dwelling photovoltaic self-consumption system open design and operation; making this study case reproducible, transferable and available for benchmark.

Practical Implications

Building simulation practitioners should consider using open data and models capitalised as ORUCE in order to collaborate and to maintain optimal performances on the whole building life cycle.

Introduction

In the current context of struggle against climate change, it is crucial to reduce the environmental impact of our energy use (Edenhofer et al. 2014), about a third of which comes from the building sector. Energy modelling can be put to good use at district level for understanding and sizing new energy systems with low carbon sources, as well as managing weather-dependent renewable energy flows with variable consumption profiles. It is now essential for the scientific community to study resilient and sustainable energy systems, but it is similarly important to do so openly.

In the building sector, many tools and projects put into practice Open Source principles for district scale energy studies, among which TEASER for urban energy modelling (Remmen et al. 2018), and oemof, Calliope, URBS or OseMOSYS for multi-scale energy systems (Grimoldi 2018). The aim of this article is to show the interests of open energy modelling for the building sector energy transition, and to propose a tool-independent methodological approach for building stakeholders to easily apply open energy modelling process and principles. The methodology focuses on use cases that appear to be good vectors for openness and reproducibility. Thus they are at the heart of the proposed Open and Reproducible Use Cases for Energy (ORUCE) methodology.

After underlining the importance of open energy modelling, this article will present the ORUCE methodology as well as the used open energy modelling tools, before applying the methodology on a dwelling photovoltaic (PV) self-consumption use case.

Open energy modelling

The importance of open energy modelling

Historical energy system modelling as well as the current mainstream approaches are closed and proprietary, even if open energy modelling has a promising emergence (Pfenninger et al. 2018). “Open” here refers to models code and data that can be freely accessible, used, modified, and shared by anyone for any purpose (Open Knowledge Foundation 2015).

Generally speaking, open energy models and data lead to an improved quality of science through transparency and peer reviewing, thus preventing errors (Pfenninger et al. 2017), biases (Morrison 2018) or even fraud. The open energy models are useful, i.e. they are easily adapted and extended to new energy systems complexity, and they lower the barriers to adoption relative to conventional proprietary solutions, making the models accessible to stakeholders without the funds for commercial options (Bazilian et al. 2012). Moreover, open energy modelling reduces parallel efforts and improves collaboration between all contributing parties, in addition to improving studies comprehensibility (Cao et al. 2016). In the building sector, such practices can gather the variety of stakeholders around accessible models, from the buildings design to their renovation or end of life in order to maintain optimal performances on the whole building life cycle.

An open and reproducible research enables to share methods and quantitative work with policy makers (Pfenninger et al. 2017), when institutions are

increasingly asking for transparency and open science practices: in Europe with the deployment of the Open Science Policy Platform (Glinos 2019), and recently in the world with the Joint Appeal for Open Science (UNESCO 2020). Energy systems studies outcome are often used to shape energy policies, affecting general public: openness provides trust and legitimacy for scientific arguments in the public debate over the energy transition (Morrison 2018), and can also permit citizen involvement (Barnes 2010), which is essential to achieve successful energy transition projects.

Open energy modelling tools meet high standards and levels of maintainability, with little or no difference in quality relative to proprietary software (Bazilian et al. 2012). Remaining challenges to get to the functionalities of closed source tools exist, especially regarding optimisation solvers (Morrison 2018).

The aforementioned practices gather modellers in communities such as The Open Energy Modelling Initiative (openmod), which promotes the ideas and practices of open energy modelling.

Key principles and best practices

Open energy modelling covers a number of key principles, among which (Morrison 2018):

- Public transparency, i.e. the model is fully documented and datasets are available for inspection. It is necessary but insufficient for reproducibility.
- Reproducibility, i.e. the available code and data enable to reproduce the work and to achieve the same results with similar conclusions,
- Open development, i.e. the use of internet mediated open source development techniques and practices.

Open energy modelling is also important or even necessary to evaluate the quality of models, data, and recommendations, i.e. the suitability of the used methods and tools to answer a given research question (Hülk et al. 2018).

Best practices in open energy modelling first consist in having a full open workflow as presented by Morrison (2018); Pfenninger et al. (2018) and Hülk et al. (2018): open energy data are processed with open source code and used in models developed with free and open source software, leading to results also processed and made available openly. The study aim and assumptions should be transparent and made available explicitly. Finally, interpretations are provided in open access in the form of articles or statements. Determining what to publish openly is an essential step: some elements should obviously remain private for security, ethical or intellectual property reasons, abiding by the European Union guidelines on open access: “as open as possible, as closed as necessary”. Open or not, data sets should still comply with the FAIR (Findable, Accessible, Interoperable Reusable) principles for them to be reusable (Wilkinson et al. 2016). Apart from the aforementioned exceptions, every element of the workflow should be open legally, i.e. properly licensed, and technically, i.e. actually accessible and in keeping with recognized standards.

Self-assessment is particularly recommended to qualify and improve the openness of studies: Cao et al. (2016) propose a transparency checklist, focusing on both models and study results comprehensibility, at least by experts. Hülk et al. (2018) apply this method and propose fact sheets for the framework, models and scenarios of the studies, in order to provide a publicly available, clear and concise representation of these, since well documented open source projects can still cause information overload issues.

Finally, open digital platforms making energy data and models available can help to meet the challenges of transparency and reproducibility (Pfenninger et al. 2018). Versioned open source tools with appropriate documentation and form is a basis, while tutorials will enable the functionalities and uses of the models to be quickly grasped. An execution environment will allow direct use of the tools (Boettiger 2015). Finally, means of synchronous or asynchronous socialisation, such as forums, if used by a sufficiently broad community, make it possible to link communities of designers and users of energy models and thus to capture and disseminate both explicit and tacit knowledge. Such platforms enable the creation of communities, transparency and legitimacy of studies and participation.

Based on the previous literature review, we propose in this article a methodology centred on use cases in order to easily apply open energy modelling best practices in the building sector.

ORUCE methodology

The Open and Reproducible Use Cases for Energy (ORUCE) methodology is presented for the first time in this article. It is thought as a transferable workflow to make open energy modelling principles and advantages accessible, whatever the energy model or framework. It is proposed by the authors based on the literature on open energy modelling best practices, with a focus on use cases as good vectors for reproducibility in district energy studies. A simple example of the methodology use is provided in the next section.

A diagram of the ORUCE methodology, as well as associated workflow and stakeholders is presented in the Figure 1. First, data points should be collected from open data sources such as public institutions, research institutes or public crowdsourcing as suggested by Bazilian et al. (2012). Associating data points with metadata is key, especially to make data FAIR. It puts data into context, with: administrative (who collected, where, permissions, etc.), descriptive, structural (organisation, formats), reference, provenance and statistical metadata. The data sets are the inputs in the ORUCE methodology, and can enrich laboratories open databases. Since the whole workflow is open, both energy modellers and building sector stakeholders (design offices, architects, public authorities, lessors, users, etc.) can choose the aim and assumptions of the study, depending on the life stage of the building, from its design to its end of life.

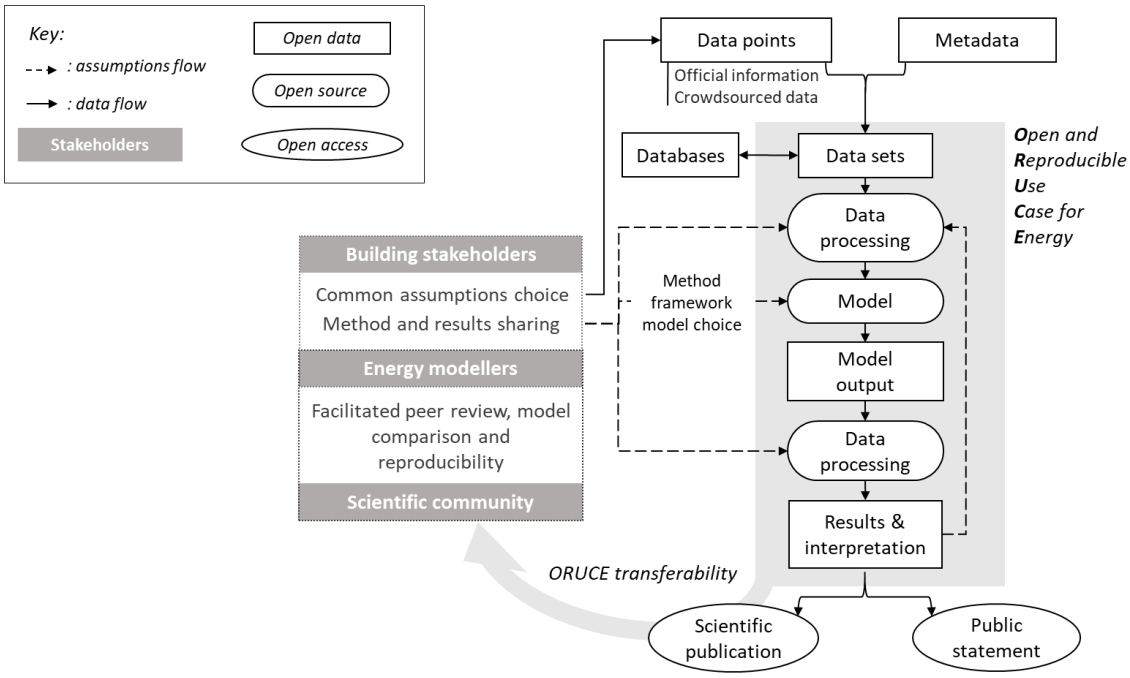

Figure 1: ORUCE methodology diagram with associated workflow and stakeholders

The assumptions are clearly stated and affect the input and output data processing as well as the model. This clear statement makes the assumptions influence on results transparent: the assumptions are propagated the same way uncertainties can be.

The raw datasets need to be processed for them to serve as model inputs: this process is made available as open source code. It is then the energy modellers' expertise as well as the commonly chosen aim and assumptions of the study that will lead to a choice of method (direct or indirect problem, optimisation method choice, etc.), free and open source software and finally, open model. The raw model output is then also processed through open source code to provide the study results and interpretation. This process from input to results is not actually linear but generally needs several iterations before accessing final results.

The proposed ORUCE methodology emphasis on the use case, i.e. the open process going from the original raw data sets to the results and interpretation on a given study. Capitalising use cases enable to keep track of the whole analysis story and to link open energy modelling practices in a comprehensive and reusable way. Not only the results and interpretation of a study are provided, but also the way they were obtained: the open data sets and processing are available, as well as the open model in the version in which it was used, with the aim and all of the assumptions of the study. The use cases are capitalised in Jupyter Notebooks (hereinafter referred simply as notebooks), i.e. code files detailed by means of text or image, and directly shareable, usable and modifiable by web application with no need for local environment whatever the model is. Beyond capitalisation, such notebooks can be used as intermediary object to collaborate around the use cases, thanks to the intermediate level of complexity notebooks can have compared to model or framework code and documentation. This tackles the information overload issue of open source, while retaining access to exhaustive information for all stakeholders. It should be noted that if perfect openness and quality levels are hardly reachable for a use case: offering a notebook for exchanges and collaboration enables continuous improvement on both those aspects.

Finally, articles as well as statements based on the results and interpretation of the study should be provided in open access, and linked to the use case notebooks, thus benefitting from the aforementioned advantages and facilitating peer review, model comparison and generally speaking, reproducibility. The transferability and use of an ORUCE for other studies serve the extension of the methodology.

Open energy modelling tools: OMEGAlpes & NoLOAD

In the following part of this article, we present an application of the ORUCE methodology, where two free and open source energy modelling tools are used. First NoLOAD, an optimisation tool developed for the design of energy components and systems using automatic differentiation. In the study, it enables to achieve non-linear optimisation using Sequential Quadratic Programming algorithm for the sizing of the energy system. Then, OMEGAlpes (Pajot et al. 2019) is a linear optimization tool designed to easily generate multi-carrier energy system models. Its purpose is to assist in developing district energy projects by helping the generation of MILP optimisation models for design and operation in pre-studies phases. Here, it allows to figure the optimal battery management out and to observe the dynamic of the energy flows.

Both are developed in Python in the G2Elab with the licence Apache 2.0. Thus, the models are directly available and modifiable to lead various optimisations

depending on users' assumptions, objectives and constraints. The users can also tap and distribute their results and contribute to the code open development, making way for scientific reproducibility in the energy field.

A dwelling photovoltaic energy self-consumption use case

Interest of self-consumption

In their review of PV self-consumption in buildings, Luthander et al. (2015) suggest that "an important further step for the research in this area is to make more comparable studies for more representative samples of buildings and end users". This, in addition to the rather emblematic aspect of photovoltaic (PV) self-consumption in district scale energy modelling, its interests regarding the energy transition, and the current favourable political context with new European regulations defining citizen energy communities makes PV self-consumption in buildings a relevant use case for applying the ORUCE methodology.

Increasing the share of renewable energies covering our energy consumption has been identified as one of the pillars of an energy transition to combat climate change (Edenhofer et al. 2014). The installation of PV panels on energy consumption sites makes it possible to increase the self-consumption rate of this photovoltaic electricity, i.e. the share of production consumed locally. Self-consumption enables to reduce the constraints on the distribution networks due to the deployment of decentralised production sources, to reduce electricity transmission and distribution losses and to improve the profitability of grid-connected PV systems. Moreover, it tends to make producers aware of their electricity consumption through potentially virtuous behavioural responses to PV systems installation (Luthander et al. 2015). Self-consumption operations thus encourage the general deployment of photovoltaic energy sources. However, the PV panels and power electronics, as well as the potentially associated batteries, have environmental impacts at different stages of their life cycle, from the extraction of raw materials to end-of-life management. Thus, a trade-off becomes necessary between self-consumption rates and environmental impact. Moreover, the optimal battery management must be addressed in order to access representative power flows relative to the operational objectives.

In the following sections, we present a dwelling PV self-consumption use case from an early stage design perspective. First we carry out a two-objective optimisation in order to maximise the coverage of local consumption by photovoltaic electricity on the one hand, and to minimise the environmental impact of the energy system over its entire life cycle on the other hand. Then, an optimal power flows management is applied to the obtained energy system design. The study focuses on one single representative building with PV panels and battery storage within the framework of a self-consumption operation. It does not explore other relevant means to improve self-consumption rates, such as Demand Side Management, or other storage technologies ranging from other battery chemistries, to hydrogen for inter-seasonal storage, to heat storage.

Origin and processing of the data sets

All the input data for the energy model comes from open databases, and is therefore directly accessible:

- The annual electricity consumption profile is modelled using the so-called "RES1" typical profiles of the residential sites for the year 2019, available on the website of the French Distribution System Operator Enedis. We consider an average electricity consumption of 4586 kWh per year and per household, calculated from the number of households connected to the French power system according to the French Energy Regulatory Commission (CRE), and the final electricity consumption of the French residential sector.
- The direct and diffuse solar irradiance data for the year 2019 are extracted from a weather station located on the roof of the GreEn-ER building in Grenoble, which houses the G2Elab laboratory and the ENSE3 engineering school. These data are made available on a server and a visualization platform[1]. From these irradiance profiles, as well as the surface, azimuth and tilt values of the PV panels, it was possible to calculate the photovoltaic production profiles with the model presented by Nguyen et al. (2019).

These data sets are also grouped together and made available with the source code.

In order to reduce the number of optimisation variables, a clustering process was carried out on the aforementioned annual consumption and irradiance profiles. Here, clustering enables to extract representative days and associated weights from a set of data over a whole year. It is a method adapted to the reduction of the study period and therefore of the number of variables for energy optimisation on a building scale (Sayegh et al. 2019). The typical days obtained from the irradiance data in Grenoble and average French consumption in 2019 are the 4th of January, 29th of August and 27th of November with weights of 50, 180 and 135 days respectively. These days are typical of a winter day, a summer day, and a day in the spring or autumn close to winter.

Energy and environmental models

The aim of this study is to apply the ORUCE methodology with open and usable energy models, allowing users to vary the data, hypotheses and objectives, or to refine the model. Thus, a simplified model with low computation time was preferred for the system design with NoLOAD:

[1] Grafana visualisation platform: https://mhi-srv.g2elab.grenoble-inp.fr/grafana/d/VnkHFo6mk/dashboard

first, clustering was used to simply provide three representative days for irradiance and consumption profiles, and then, the battery control dynamics were not considered here because of the periodic evolution of the profiles, considering a charge-discharge cycle per day. The energy stored over a day is then considered as a scalar calculated for each typical day, where the PV power and consumption are time series at hourly time steps. Imports and exports to and from the power grid are thus calculated for each typical day as follows:

$$exp = \sum_{h=0}^{23} \max(P_{PV}(h) - P_l(h), 0) - eff_{sto} * e_{sto} \quad (1)$$

$$imp = \sum_{h=0}^{23} \max(P_l(h) - P_{PV}(h), 0) - eff_{sto} * e_{sto} \quad (2)$$

with *exp* and *imp* respectively the exports and imports on the power grid over a single day, P_{PV} and P_l respectively the PV and load powers at hourly time steps, eff_{sto} the storage efficiency, considered identical for the charge and discharge, and e_{sto} the storage energy charged for the export calculation, and discharged for the import one. Imports and exports are constrained to take positive or zero values.

The battery capacity will then be determined as the maximum e_{sto} value for the different typical days, integrating the limits of depth of discharge, here considered equal to 50% (lead-acid technology).

The used coverage indicator is the Load Cover Factor (LCF), i.e. the share of electricity consumption covered by local production (Salom et al. 2014). In our case, the LCF is calculated for each typical day as follows:

$$LCF = \frac{E_{load} - imp}{E_{load}} \quad (3)$$

with E_{load} the energy in Watt-hours consumed by the household during one day. Using the LCF indicator alone will maximise the PV production to cover the local consumption. A "*non-LCF*" indicator has been defined as an objective to be minimised for the design optimisation model. It includes the LCF indicator over the various typical days, representative of a full year:

$$non - LCF = \sum_{0 \le d < nb\ days} \frac{w_d}{365} * (1 - LCF_d) \quad (4)$$

where *nb_days* is the number of typical days, w_d the weight of each typical day, i.e. the number of days the typical day represents, LCF_d the Load Cover Factor for each typical day.

The optimisation variables of the model are the surface area of the PV panels and their tilt and azimuth that will enable to calculate the PV output, and the energy stored for each typical day, which will give the value of the battery capacity. The panel areas are constrained between 1 and 21m² and the stored energy is constrained to be less than 1 kWh.

In the MILP energy model used with OMEGAlpes, the dynamic behaviour of the battery is considered but its sizing is fixed: the only optimisation variables are the battery charging and discharging powers over the considered study period. The objectives are to minimize battery losses and the imports from the power grid. The OMEGAlpes model is accessible via the study notebook[2], and the MILP formulation can be found in OMEGAlpes online and open source code and documentation.

The environmental impact indicator chosen for this case study is the Global Warming Potential (GWP) expressed in kilograms of CO_2 equivalent (kg CO2eq), which takes into account the radiative forcing effects accumulated over a given time horizon, related to greenhouse gases (GHG) emissions into the atmosphere over the entire life cycle of the energy system components (Stocker et al, 2013). The functional unit considered for this study is defined as follows: consuming electricity according to a given profile for 30 years, with a 4586 kWh yearly consumption, using electricity from the grid and from a PV panel and battery system. The GWP indicator is therefore calculated as follows:

$$GWP = GWP_{PV} * area_{PV} * \frac{duration}{lifeespan_{PV}} + GWP_{bat} * capacity_{bat} * \frac{duration}{lifespan_{bat}} + emissions_{grid} * imports_{grid} \quad (5)$$

with:

- *GWP* the Global Warming Potential of the energy system (kg CO_2 eq.),
- GWP_{PV} the GWP of PV panels, inverters and connectors per unit of PV area (710 kg CO_2eq/m²)[3],
- $area_{PV}$ the PV panel area (m²),
- *duration* the study duration, here 30 years,
- $lifespan_{PV}$ the PV panels lifespan (30 years),
- GWP_{bat} the GWP of the batteries per capacity unit (0.146 kg CO_2 eq./Wh)[3],
- $capacity_{bat}$ the battery capacity (Wh),
- $lifespan_{bat}$ the battery lifespan (3 years),
- $emissions_{grid}$ the GHG emissions due to the electricity consumption from the power grid over the whole study, per consumed energy unit (kg CO_2eq/kWh). To guard against the particular French electricity mix and CO_2 emissions, the average European grid electricity emissions (0.296 kg CO_2eq/kWh)[4] are considered.
- $imports_{grid}$ the grid electricity consumption of the dwelling for 30 years (kWh).

PV electricity injected into the grid is not understood here as GHG emission removal because it goes beyond the

[2] To access the notebook from OMEGAlpes Gitlab repository: https://gricad-gitlab.univ-grenoble-alpes.fr/omegalpes/omegalpes_examples/-/blob/BS2021_last_review/notebooks/article_2021_BS_ORUCE.ipynb

[3] LCA open data base: https://www.base-inies.fr/iniesV4/dist/consultation.html

[4] European Energy Agency: https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity

https://doi.org/10.26868/25222708.2021.30721

functional unit, for which we stand from a consumer's point of view. The GWP values presented are subject to strong uncertainties: they allow a relative and non-quantitative study for the minimisation of GHG emissions from the energy system. Generally speaking, the GWP objective takes into account the environmental impact of the PV panels and batteries compared to grid electricity emissions in the system sizing: it is complementary to the sole LCF objective that tends to maximise PV and battery sizing for local energy coverage.

Results of the study case

Before accessing the final results to communicate, several iterations from raw data to results were necessary. Such iterations, mentioned in the ORUCE methodology, enabled to choose relevant:

- optimisation parameters: precision, number of iterations;
- objectives: Load or Supply Cover Factor, GWP or other environmental indicator;
- limits on variables: PV panels area, battery capacity.

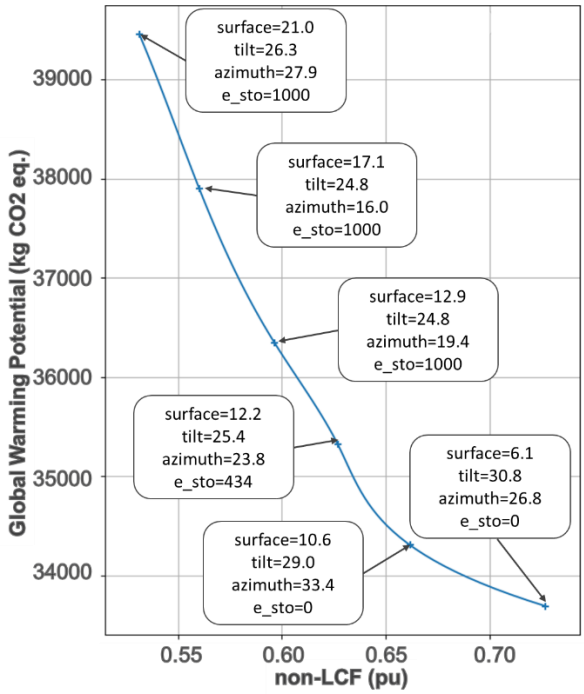

Figure 2: Pareto curve where non-LCF and GWP indicators are minimised for a dwelling PV self-consumption study case

The Figure 2 presents the results in the form of a Pareto curve between the GWP on the y-axis and the non-LCF indicator on the x-axis. The optimisation variable *e_sto* corresponds to maximal storage energy of typical days. A slight bend can be observed when the non-LCF indicator falls below a value of about 0.65. It is noticeable that it is from this point that the capacity of the batteries and the surface area of the PV panels increase both. In addition, the azimuth values here remain relatively constant with a South - South-East orientation, which would therefore be optimal for covering the consumption profiles with PV production.

In the end, the compromise between self-consumption and GWP for a self-consumption operation depends on the user's choice. The following sizing is arbitrarily chosen for the energy system: a PV panel surface of 12.2 m² with a tilt of 25.4° and an azimuth of 23.8°, with *e_sto* equals to 434 Wh, i.e. a battery capacity of 868 Wh.

After implementing this design in the OMEGAlpes model of the study, the results of the battery management over a chosen period of time can be put in place, and the energy flows of the system can be observed. For study periods higher than 3 months, the used CBC open source solver does not perform well and the computing time is too long: professional solvers should be used. Figure 3 presents the energy flows in the dwelling energy system on the typical august day work week of 2019. If the battery management here is somewhat trivial, the OMEGAlpes model is accessible for more intricate studies on this energy system.

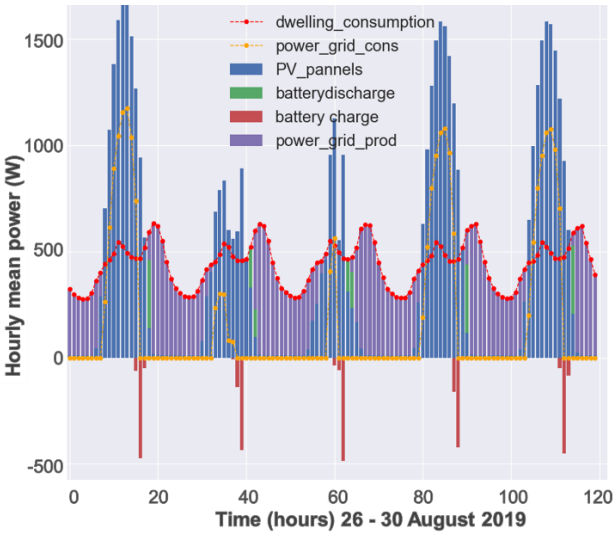

Figure 3: Dwelling energy flows diagram from OMEGAlpes

The notebook for this study has been developed, and can be updated depending on the study case progress. It can be accessed online without installation of an environment, via the Mybinder public service to directly use and potentially adapt the code and input data. The ORUCE methodology offers here the possibility to adapt the case study to different situations, e.g. by varying the battery or PV panel technologies, or selecting input data depending on the new study characteristics and taking into account uncertainties. It also enables to benchmark different energy models, methods of study period or model reduction, and optimisation techniques.

Regarding the limits and perspectives of this case study, a more refined analysis of the clustering results could be carried out, and time steps below one hour would give more accurate results. More refined modelling hypotheses could also be adopted over the 30 years considered for the design, such as the ageing of batteries and PV panels or changes in energy mixes. In addition, part of the power demand could be managed to reflect a possible adaptation of consumption to local production. Future work could also include a battery management depending on dynamic

power grid GHG emissions. It would also be interesting to carry out the study at the neighbourhood scale in order to qualify and quantify the consequences on the energy networks, to evaluate the relevance of the sizing with the indicators presented here, and to integrate energy community issues. Such limits and perspectives are further arguments for the appropriation of the use case and collaboration with the ORUCE methodology. Finally, it is obvious that this example is a very simplified one that does not take into consideration stakeholders. Actual district scale energy projects involve complex energy systems and actors' interactions, with potentially closed data or models. The ORUCE approach in such case allows for transparency on data sources and availability, in addition to providing an intermediary object for discussion in the stakeholder group, inviting to adopt open energy modelling practices with the show of its interests.

Discussion

Various limits and numerous perspectives have been identified for the ORUCE methodology, and generally speaking, open energy modelling.

Regarding, open energy modelling, it has a few pitfalls, particularly in the academic world (Morrison 2018): the principle of open and regular availability of research results runs counter to research habits where teams tend to want to preserve their academic reputation by only giving access to perfectly finalised work. Moreover, the methods of research funding can make it difficult to promote work based on the open work of other research teams. Finally, a more widespread use of open methods faces a certain institutional inertia in the absence of incentives. The lock-in to proprietary models as well as the lack of awareness and practical knowledge regarding open practices are additional issues (Pfenninger et al. 2018), that this article aims at tackling.

Compared to closed approaches, the ORUCE methodology presented in this article enables to go beyond the results alone: it puts the data and models in the use case context, underlining the dependencies of the results. It fosters trust and collaboration between stakeholders, and enables to avoid errors and biases. The use cases are accessible, usable and transferable for possible future work and benchmark.

The ORUCE methodology is a first proposal and needs to be put into practice to a greater extent, which would enable to qualify its transferability process and interests. Stakeholders' roles and interactions in the workflow could also be better defined. The formalism regarding the linkage between open access publications and notebooks needs to be addressed, with the issue of the durability of the hosting platforms.

Further work will focus on setting an open and collaborative platform up to provide a library of ORUCE, as well as questioning its design with social experiments based on a Sociology of User Experience Approach.

Conclusion

This article underlines the importance of open energy modelling for district scale studies, in a context where it is increasingly needed and asked for. It presents open development best practices, and provides the ORUCE methodology, illustrated with a dwelling PV self-consumption example to show its actual application. The ORUCE methodology is a workflow from open data to open model formulation and solving, which capitalises the study as a use case, an intermediate object for the stakeholders to collaborate. Clearly stated assumptions, open data and open energy models collected in the use case make the studies easily reproducible and transferable. It shows easy to apply practices in order to make open energy modelling common within the building simulation community. Beyond transparency and open science regulation, such practices can entail to seize open science advantages for relevant and useful collaborations.

Acknowledgement

This work has been partially supported by the CDP Eco-SESA receiving fund from the French National Research Agency in the framework of the "Investissements d'avenir" program (ANR-15-IDEX-02).

The authors also thank the openmod community for the insightful online and face-to-face exchanges.

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