RECsim—Virtual Testbed for Control Strategies Implementation in Renewable Energy Communities

RECsim – Virtual testbed for control strategies implementation in Renewable Energy Communities

Antonio Gallo[1[0000-0003-4794-6015]], Marco Savino Piscitelli [1[0000-0002-0013-5656]], Lorenzo Fenili[2] and Alfonso Capozzoli [1[0000-0002-0083-4983]]

[1] Department of Energy (DENERG), TEBE Research Group, BAEDA Lab, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Turin, Italy
[2] ABB Smart Power Electrification, ABB SpA

Abstract. In recent years, the building sector has been pointed out as critical for the energy transition, and the Energy Communities have been introduced to allow the aggregation of multiple buildings to jointly manage their energy generation and consumption. At cluster level, buildings can provide flexibility services to the energy grid by coordinating the energy consumption in order to match local energy generation. The aim of this work is to present a virtual testbed for the implementation of control strategies in Energy Communities and the assessment of their performance under different climatic conditions, generation systems, penetration of renewable energy sources or availability of energy storage. The virtual environment embeds models of the thermal building dynamics and of various systems and it is wrapped into an OpenAI gym to easily allow the implementation of advanced control algorithms such as reinforcement learning.

Keywords: Energy Community, building energy management, virtual environment

1 Introduction

European Union has included in the Clean Energy Package several directives such as the Energy Performance of Building Directive and Renewable Energy Directive to reduce the energy intensity in the building sector. These directives push toward the improvement of building envelope and energy system performance, the liberalization of the electricity market for small producers and the penetration of Distributed Energy Resources (DER). In this context, Citizen Energy Community and Renewable Energy Community emerged as powerful instruments to involve prosumers at actively balancing the energy demand and supply at the distribution level by jointly operating with the other actors of energy grid. The shift towards a distributed approach for the management of the energy grid is however related to the increased complexity of such systems. Bi-directional energy flows, DER, Electric Vehicles (EVs), energy storage technologies together with data analytics-based and Information and Communication Technologies have opened the door to new possibilities for achieving a flexible energy demand giving to prosumers more influence than ever before in reaching energy efficiency and economic goals. Literature highlighted the importance of building energy flexibility also to address grid stability problems, especially if the energy fluxes are managed at a higher level than single building. In fact centralized and distributed architectures that also exploits peer-to-peer energy trading schemas may achieve better results. Advanced control strategies for the energy management of cluster of buildings are being introduced in the literature, and in many cases for their in-field implementation is required an off-line development phase that leverages digital twins of buildings and energy systems for the training of control strategies and for assessing their potential impact according to different objective functions. For this reason, the development of virtual environments for the conceptualization and testing of control strategies for energy management in Energy Communities (ECs) has become a relevant research topic.

A few tools and methodologies have been already developed for this purpose and some of them are briefly introduced and described. In [1] the virtual environment CityLearn is introduced. CityLearn is a virtual testbed for the specific implementation of Reinforcement Learning (RL)-based control algorithms for urban energy systems wrapped using OpenAI Gym library. The environment allows to consider as controllable systems Heat Pumps (HPs), an active Thermal Energy Storage (TES) and a Battery Energy Storage Systems (BESS) and photovoltaic (PV) systems as uncontrollable generation, while the thermal demand is pre-computed, thus not making it possible to exploit the building thermal mass as a flexibility source in the control problem. Pinto et al. [2], adapted the CityLearn environment introducing a data-driven approach for modelling the thermal dynamics of the buildings. A Long-Short Term Memory neural network was used to predict the indoor temperature trajectory associated to a simulated control signal, with the opportunity to feed the prediction model also by using monitored data. This approach allows to control the indoor air temperature but still relies on the availability of data or the development of a physics-based model for each building.

Also, Pigott et al. in [3] proposed an adaptation of the CityLearn environment for the evaluation of voltage levels across the distribution grid. This was done by exploiting the pandapower library from Python to simulate the Alternating Current (AC) distribution grid that connects each building to demonstrate the applicability of advanced controllers for the prevention of undervoltage and overvoltage events.

Sen et al. [4] developed a virtual environment for a real Net Zero Energy Community in Florida using the simulation tool Modelica for the control of thermostat setpoints in buildings. The environment includes both physics-based and data-driven models that are validated against measurements. Particularly, this testbed allows to consider cluster of buildings with different end-uses such as office, residential, and retail buildings, and PV systems as DER. However, the high-fidelity physics-based models need non-negligible simulation time that constraints the application to small clusters of buildings.

Modelica and EnergyPlus are combined through a Functional Mock-up Interface in Scharnhorst et al. [5], where 11 buildings with HVAC system and HPs are considered. The models were calibrated with operational data from real buildings with different end-uses. The main limitations are those related to the adoption of high-fidelity physics-based models as previously discussed. Jin et al [6] developed a virtual environment for an urban complex to test scheduling and control strategies for the operation of HVAC systems in multiple buildings. The environment includes a detailed physical model of the HVAC system of each building and considers the thermal dynamics of the building envelope. The thermal parameters are evaluated for four typologies of buildings that are considered to be characteristic in the analysed urban complex.

Another example is proposed in. [7], where a comprehensive virtual environment is developed considering models for estimating both energy demand and generation in a cluster of buildings. In particular, with physics-based models, are simulated the thermal load profiles for thermal zones, the electrical load profiles, a generation profile for PV and wind-turbine, an aggregated Plug-in Electric Vehicles (PEV) load profile, the operation of a central Energy Storage System (ESS), and the operation of an MV/LV distribution system interconnecting the buildings and the main grid. The environment allows to test control strategies for the optimization of the HVAC system operation of each building thermal zone and the power exchange scheduling between PEVs and the central ESS with the distribution grid. The models for the simulation of the building thermal dynamics adopted in [6] and [7] consider a reduced number of parameters, but it is still not suitable for large cluster of buildings.

An interesting example on how to efficiently scale up the virtual environment is proposed by Wang et al. [8]. A simplified grey-box approach based on RC models was used to simulate the thermal dynamics of individual buildings for very large clusters. The proposed tool was developed as an open-source simulation-based virtual environment to train and validate control algorithms for thermostatically controlled load coordination. The key aspect of this environment is that it only needs two thermal parameters for the building envelope, that can be inferred from a real dataset and assigned to each building in a way that replicates the same distribution that they have across the building stock. However, measurements only come from residential buildings, and it is only allowed the testing of ON/OFF control strategies for HVAC systems.

From the literature review emerged that among the available virtual environments are still present issues related to the detail of simulations, computational costs and scalability. However, each of them was suitable for addressing the specific objective for which was designed. In this perspective, this study introduces the virtual environment RECsim that is specifically targeted for the simulation of energy management strategies in ECs allowing the analyst to set the control problem with the highest flexibility as possible. The main features of RECsim are related to the capability of the environment to simulate the building thermal dynamics, to scale the control problem up to large communities, to consider control actions more sophisticated than system ON/OFF and leverage simplified but accurate models of energy systems.

In particular, the simulation of the indoor air temperature is performed as in [8] in order to exploit the building thermal mass as a flexibility source to be considered in the control of HVAC system operation together with TES and BESS. In addition, RECsim allows to generate different scenarios and configurations of the EC to deploy the developed controllers in a variety of boundary conditions and assess their adaptive features. The level of detail ensures sub-hourly evaluation of the thermal demand of each building in the EC and allows the control of HVAC systems, and active and passive energy storage. The pvlib library from Python is used to retrieve the solar position and compute the AC electricity output of the PV modules. The electrical load was disaggregated into HP load, Electric Water Heater (EHW) load and appliances load, whereas the gas load only accounts for the gas-fired boiler when available. The key features of RECsim can be then identified as follows:

- Grey-box dynamic model of the built environment validated against real measurement for sub-hourly simulation of the indoor air temperature according to [8]
- Fast implementation of a large cluster of buildings with diversified energy systems and envelopes
- The environment built on Python does not require any other software to be run and it is wrapped into the OpenAI gym library for the implementation of RL control
- The environment is composed of several sub-modules, so that it is easily accessible for future improvement to expand the existing modules or to add new ones

The paper is structured as follows: Section 2. describes the simulation environment through the various sub-modules which it is composed of. Section 3 presents the case study where a Rule-Based (RB) controller is implemented in the proposed environment and whose results are reported in Section 4. The last section includes the conclusions of the work and introduces the related future works.

2 Description of the simulation environment

The simulation environment is completely developed in Python, and it follows the OpenAI Gym framework which is a standardized interface for control-oriented simulation. The initialization is done by calling the *RECsim()* Python class and feeding the input parameters that are grouped by three categories which are: *simulation*, *building* and *energy system*. Before the starting of each control episode, the *reset()* function is called to reset Key Performance Indicators (KPIs), and storage SoC, and then the *step()* function implements the control action.

2.1 Definition of building thermal model

A grey-box approach is adopted to evaluate the thermal demand of each building included in the environment. It has been chosen the RC model from [8], which is tuned using real data of indoor air temperature and HVAC operation collected for a very large sample of residential buildings in the United States (ECOBEE dataset). The thermal properties of each building are lumped into two parameters inferred from ECOBEE dataset that are the thermal time constant τ and the equivalent heat gain temperature $T_{HG,eq}$. Each building is considered as a single-zone building where only one temperature is representative of the thermal comfort and it is indicated as T_{in}. The reduced model to compute T_{in} at the next time step is expressed by Eq. (1-4):

$$T_{in,t+1} = e^{-\Delta t/\tau} \cdot T_{in,t} + (1- e^{-\Delta t/\tau}) \cdot (T_{out} + HG_{int} + HG_{sol} + R \cdot \mu + R \cdot E_{th,load}) + \varepsilon \quad (1)$$

$$HG_{int} = T_{HG,eq} \cdot HG_{ratio} \cdot HG_{int,sched} \quad (2)$$

$$HG_{sol} = T_{HG,eq} \cdot (1-HG_{ratio}) \cdot HG_{sol,sched} \quad (3)$$

$$R = (\tau \cdot RC_{ratio})^{1/2} \tag{4}$$

Where Δt is the time step, T_{out} is the outdoor air temperature, $E_{th,load}$ is the thermal input to the thermal zone from the HVAC system, μ is the modeling uncertainty, ε is the measurement error, RC_{ratio} is the ratio between the thermal resistance R and the thermal capacity C and HG_{ratio} is the ratio between the internal heat gain and the solar heat gain. $HG_{int,sched}$ and $HG_{sol,sched}$ are daily schedules for the internal and solar heat gain and are available according to the reference building developed by the U.S. Department of Energy or inferred from the ECOBEE dataset.

2.2 Estimation of Domestic Hot Water load

The use of DHW is influenced by many factors such as location, occupant behavior and economic condition, even though, typical daily and seasonal patterns can be identified. The methodology adopted in the RECsim environment was inspired from Jordan et al. [9], that defined the probability of a DHW event as in Eq. (5):

$$p(t) = p_{day}(t) \cdot p_{week}(t) \cdot p_{season}(t) \tag{5}$$

Where $p_{day}(t)$ is the probability distribution of DHW event across the day, $p_{week}(t)$ is the distribution of DHW consumption among weekdays and weekend and $p_{season}(t)$ is the seasonal variation across the year. In this case, holidays are not considered. Typical daily profile and weekend/weekday ratio are available in [9] and [10]. The seasonal variations can be expressed as a sine function over the year.

The flowrate of each DHW event is sampled from a Gaussian distribution, and then it is associated to the energy consumption according to Eq. (6):

$$E_{DHW} = \rho \cdot c_p \cdot V \cdot (T_{mains} - T_{DHW}) \tag{6}$$

Where ρ and c_p are the density and the specific heat of the water at 15 °C, V is volume of water requested by the DHW event, T_{mains} is the water temperature from the distribution network, and T_{DHW} is the supply hot water temperature. At the current stage these temperatures are considered constant since they can be included in the seasonal variations. The average daily DHW consumption for each building is sampled according to a Gamma distribution.

2.3 Estimation of the appliances load

Typical daily profile for appliances electrical load is provided in [10], which is used to sample values of hourly demand. The average appliance daily electricity consumption for each building is sampled according to a Gamma distribution, while the actual daily consumption is computed by Monte Carlo estimation of the area under the daily profile and then it is spread across the whole day accordingly.

2.4 Definition of the Heat Pump model

Each building in the environment is supposed to be equipped with an Air-to-Air HP which is sized according to the maximum thermal load. The thermal capacity is considered constant, whereas the COP is a function of temperature difference between the outdoor air temperature and the supply temperature as in [11]. The supply temperature for the cooling and heating season is an input parameter of the environment, and it is constant during each season. Eq. (7) reports the COP function:

$$COP = 6.81 - 0.121\,\Delta T + 0.00063\,\Delta T^2 \tag{7}$$

2.5 Definition of Gas-fired/Electrical heater model

Two options for the production of DHW are implemented. Both are considered as non-flexible loads, thus the generation matches the consumption at each simulation time-step. Each building considered in the environment could be equipped with one of those generation systems which are characterized by different energy carriers and by different efficiencies.

2.6 Definition of the PV model

The output of the PV modules is obtained by using the pvlib library from Python. This library allows to simulate a system composed by the PV panel and the inverter that is connected to the main grid. For the sake of brevity, the reader is reminded that an extended documentation is available at [13].

2.7 Definition of thermal and electrical storage model

Let us denote E_{BESS} as the energy exchanged between the storage and the thermal/electrical system and ΔE_{BESS} the variation of the available energy in the storage. Then the SoC model is represented by Eq. (8-9):

$$\Delta E_{ESS} = E_{ESS} \cdot \eta_{charge} \quad if \;\; E_{ESS} > 0 \tag{8}$$

$$\Delta E_{ESS} = E_{ESS} \,/\, \eta_{discharge} \; if \;\; E_{ESS} < 0 \tag{9}$$

Moreover, technical constraints are considered for the SoC state and for E_{BESS} as reported in Eq. (10-11):

$$E_{ESS,min} < E_{ESS} < E_{ESS,max} \tag{10}$$

$$SoC_{min} < SoC < SoC_{max} \tag{11}$$

Eventually, the energy exchanged is limited according to the available energy for charging and to the thermal and electrical demand. TES operation is constrained by the HP thermal capacity and the building thermal load as in Eq. (11-12) while the BESS cannot exchange electricity with the main grid, and it is expressed in Eq. (14-15).

$$|E_{TES}| < |E_{HP,max}| - |E_{th,load}| \quad if \;\; E_{TES} > 0 \tag{12}$$

$$|E_{TES}| < |E_{th,load}| \qquad if \;\; E_{TES} < 0 \tag{13}$$

$$|E_{BESS}| < |E_{PV}| - |E_{el,oad}| \qquad if \;\; E_{BESS} > 0 \tag{14}$$

$$|E_{BESS}| < |E_{el,load}| \qquad if \;\; E_{BESS} < 0 \tag{15}$$

2.8 Action space

The RECsim environment has been designed to allow the control of the thermal energy delivered to the building, the hot and cold TES and BESS. These variables can assume continuous values in the range [$Q_{cooling,max}$, $Q_{heating,max}$], [-0.33 C_{TES}, 0.33 C_{TES}] and [$P_{BESS,max,\ discharge}$, $P_{BESS,max\ charge}$] where Q is the thermal load, C_{TES} is the TES thermal capacity and P_{BESS} is the BESS power exchange. During the simulation, the actions taken by the controller under analysis are verified according to physical constraints and then actuated.

2.9 Reward function

The objective function is defined by the user among those terms available in the environment, which are evaluated both at building and community level. The user can specify whether to optimize a single term or a linear combination of multiple terms according to weights defined by the user itself. The available terms are the energy cost and consumption at building and community level, the comfort violations, and the shared electricity. The shared electricity is computed as the minimum between the renewable generation and community energy consumption.

2.10 Rule-Based control

The RECsim environment is provided with three reference rule-based control logics that are independent between each other. An RB thermostatic control is implemented to keep the indoor temperature in a pre-defined comfort range. During the heating season thermal energy is delivered to the building by the HP or by the TES when the indoor temperature is below the lower acceptability range, and it is increased up to the upper limit of the comfort range. The TES control strategy aims at decreasing the peak load by shifting load toward off-peak hours. During low-price periods, the TES is charged by the HP until its complete charge, whereas during peak-price periods the TES is discharged whenever thermal energy is required by the building and the SoC is higher than 0. A simple RB control strategy for the BESS was inspired by [12]. When a PV surplus occurs, the BESS is charged otherwise it is discharged. Moreover, the constraints on charging/discharging power and on SoC have to be respected. This means that during the charging process, if the BESS cannot store all the excess electricity, the overproduction is injected in the grid. During discharging events, if the electricity from the PV and the BESS does not match the building electrical demand, the electricity is drawn from the main grid.

3 Case study

An example of the implementation of the reference control strategies in RECsim is provided in this section. The baseline also provides a benchmark for the comparison with the tested control strategies. The simulation is set up for 50 residential buildings in Miami (FL) for 1 month during the cooling season from 01/08 to 31/08 with a simulation time-step of 5 minutes. Four different price schedules for buying electricity from the grid are implemented, and they are assigned to each building according to the parameters in the file "*electricity_schedule.json*". Weather data is downloaded from the pvlib module in Python where Typical Meteorological Year is available based on building location. The cost weight is not used here since the RB Control does not have an objective function to be minimized/maximized. The comfort range for the indoor air temperature is selected according to the ASHRAE Standard 55-2017 that identifies 23.95 °C and 26.85 °C as lower and upper limit of the comfort band respectively.

Thermal properties of the envelope are inferred from the ECOBEE dataset according to the selected building location. The supply water temperature of the cooling system is assumed equal to 7 °C for the considered operation mode. The gas price is set to 0.039 $/kWh. The penetration of PV, cold TES and gas-fired boiler in the cluster of 50 buildings was assumed to be 0.7, 0.7 and 0.2, respectively.

4 Results

In Fig. 1, the energy flows of the whole EC are aggregated and are plotted over one week of the simulation period. Similar daily patterns can be observed for both the electrical and thermal flows. Tab. 1 reports several KPIs at building and EC scale. Values range for each building from 272.4 kWh to 1301.0 kWh for the total electricity consumption. Few buildings achieved an energy cost lower than zero due to the high number of PV modules considered together with a very low electricity demand. Self-Sufficiency (SS) and Self-Consumption (SC) are computed for buildings that are equipped with PV modules to measure the share of electricity consumption that is met by local generation and the share of local generation that is consumed on site, respectively.

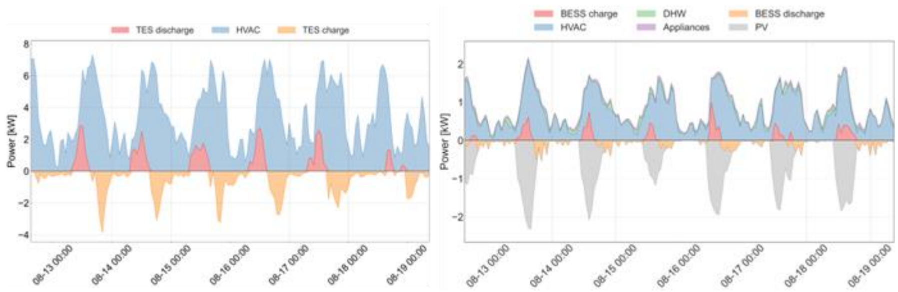

Fig. 1. Aggregated electrical and thermal balance

When the EC is considered as a whole, values of 0.46 and 0.98 for SS and SC are obtained, while on average at single building scale SS and SC are equal to 0.48 and

0.71, respectively. SC at EC level is very high since the PV generation was generally lower than the electrical demand. The daily Peak-to-Average ratio (PAR) for the EC is equal to 1.82 which is lower than the average value of 2.9 at single building.

The Flexibility Factor (FF) may assume values between -1 and 1 and measures the amount of energy consumed during off peak price periods and has no meaning when considering the whole EC because buildings can have different peak-price periods.

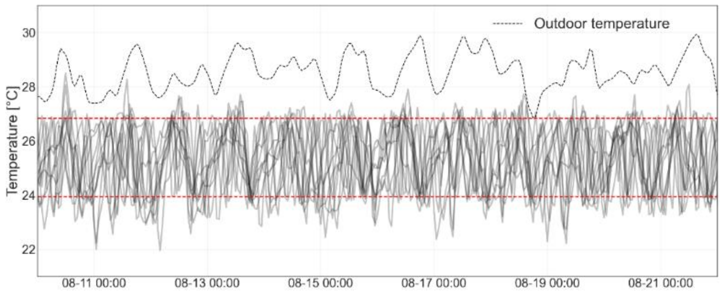

Fig. 2. Evolution of indoor temperature for each building in the EC

It shows values from 0.16 to 0.69 for the single buildings, which means that electricity is mainly consumed during off-peak periods. As shown in Fig. 2, for the considered 50 buildings, the reference RB control demonstrated its effectiveness at maintaining the indoor air temperature between the upper and lower limit of the acceptability range.

Table 1. Table KPIs for buildings and the whole Energy Community.

KPI	Min	Max	Average	Community
El. Consumption [kWh]	272.4	1301.0	679.7	33985
El. Cost [$]	-15	152.5	62.2	3109.4
Shared electricity [kWh]	-	-	-	15510
SS	0.18	0.73	0.48	0.46
SC	0.21	0.91	0.71	0.98
PAR	2.2	3.8	2.9	1.82
FF	0.16	0.69	0.48	-

5 Conclusion and future works

RECsim is a virtual environment for the simulation of EC conceived for the implementation and comparison of advanced control strategies against a reference RB control policy. The aim of this work is to introduce this new environment by describing the various modules which is composed of, to assess pros and cons of adopting it as virtual test-bed and present a first application based on rule-based control. Future works will expand existing modules and add further energy systems. Currently the building stock is composed only by residential buildings and the same RC model is used for all of them according to [8]. In the next steps, the RC model can be improved to describe a larger variety of buildings. In addition, alternative energy modeling approach (i.e, black box modeling) will be tested. Moreover, the DHW and appliances schedule can be diversified by considering the occupant types and behavior. Other thermal and electrical generation systems will be implemented such as CHP systems, chillers, or centralized renewable energy plants. Further steps will focus on the modeling and control of EVs fleet operation and lastly, on the possibility to implement a Local Energy Market inside the EC for the negotiation of the energy flows among the members.

Acknowledgment
The work of Antonio Gallo was done in the context of a Ph.D. scholarship at Politecnico di Torino funded by ABB s.p.a.

References

1. Vázquez-Canteli, J., Dey S., Henze G., Nagy, Z.: CityLearn: Standardizing Research in Multi-Agent Reinforcement Learning for Demand Response and Urban Energy Management. arXiv preprint arXiv:2012, 10504 (2020).
2. Pinto, G., Deltetto, D., Capozzoli, A.: Data-driven district energy management with surrogate models and deep reinforcement learning. Applied Energy, 304, 117642 (2021).
3. Pigott, A., Crozier, C., Baker, K., Nagy, Z.: GridLearn: Multiagent Reinforcement Learning for Grid-Aware Building Energy Management. arXiv preprint arXiv:2110.06396, (2021).
4. Huang, S., Wang, J., Fu, Y., Zuo, W., Hinkelman, K., Kaiser, R. M., He, D., Vrabie, D.: An open-source virtual testbed for a real Net-Zero Energy Community. Sustainable Cities and Society, 75, 103255 (2021).
5. Scharnhorts, P., Schubnel, B., Fernandez, B. C., Salom, J., Taddeo, P., Boegli, M, Gorecki, T., Stauffer, Y., Peppas, A., Politi, C.: Energym: A Building Model Library for Controller Benchmarking. Applied sciences, 11, 3518 (2021).
6. Xiaolong, J., Fengyu, Q., Qiuwei, W., Yunfei, M., Hongjie, J., Xiaodan, Y., Zhuoyang, L.: Integrated optimal scheduling and predictive control for energy management of an urban complex considering building thermal dynamics. International Journal of Electrical Power & Energy Systems, 123, 106273 (2020).
7. Farinis, G. K., Kanellos, F. D.: Integrated energy management system for Microgrids of building prosumers. Electric Power Systems Research, 198, 107357 (2021).
8. Wang, Z., Chen, B., Li, H., Hong, T.: AlphaBuilding ResCommunity: A multi-agent virtual testbed for community-level load coordination. Advances in Applied Energy, 4, 100061 (2021).
9. Jordan, U., Vajen, K.: DHWcalc: program to generate domestic hot water profiles with statistical means for user defined conditions. In: Proceedings of the ISES Solar World Congress, pp. 8-12. Orlando, FL, USA (2005).
10. Hendron, B., Engebrecht, C.: Building America House Simulation Protocols. DOE/GO-102010-3141(2010).
11. Staffell, I., Brett, D.J.L., Brandon, N., Hawkes, A.: A review of domestic heat pumps. Energy & Environmental Science, 5(11), 9291-9306 (2012).
12. Amato, A., Bilardo, M., Fabrizio, E., Serra V., Spertino F.: Energy Evaluation of a PV-Based Test Facility for Assessing Future Self-Sufficient Buildings. Energies, 14(2), 329 (2021).
13. pvlib python, https://pvlib-python.readthedocs.io/en/stable/, last accessed 22/02/2022.