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Research paper

# Integrated cloud platform for energy management of self-sustainable island communities

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ABSTRACT

An integral part of contemporary initiatives striving to promote and create self-sustainable communities has been the integration and efficient management of renewable energy sources, energy storage solutions, and sustainable heating and cooling assets. This paper presents a unique combination of diverse technologies, ranging from established data management solutions like SQL and NoSQL databases to custom semantic solutions and device-specific control adapters powered by the OpenMUC gateway. Additionally, it incorporates analytical machine learning-based forecasting solutions paired with optimization algorithms, working together to enable energy self-sufficiency. The platform constituted by these solutions is subsequently utilized to provide predictive and real-time control of energy assets in various facilities in line with the selected operation strategy. Its application, particularly in terms of effective energy storage utilization and timing of asset activation scheduling, ultimately results in improvements in renewable energy integration and overall increase of energy efficiency in the considered buildings. As demonstrated in real-world use cases tested within prosumer-based energy communities in geographical islands, the application of the platform resulted in tangible modifications to the primary statistical characteristics of electrical energy consumption clearly signified, among others, by a reduction in mean consumption of between 40 W and 190 W. Through scrutinizing the achieved results, it can be concluded that the platform displays the capabilities to outperform stock control algorithms provided by the inverter vendors. Expanding upon the application limited to the electric assets, use cases in the thermal domain where optimization outputs are utilized for heat pump scheduling were also discussed and presented.

## 1. Introduction

The European Union (EU) has set ambitious targets to reduce future greenhouse gas emissions. The proposals accepted in 2023 (European Commission, 2014) state that the short-term strategy for 2030 should strive to achieve 55% emission reduction in comparison with 1990 levels through changes in climate, energy, transportation, and taxation policies. Going beyond this, for 2040, the net emissions ought to be reduced by 90% with the long-term strategy (European Commission, 2021) striving for a net-zero economy when looking at 2050. In assessment of the means to achieve these climate neutrality goals, the literature outlines various strategies. For instance, European Commission and Directorate-General for Climate Action (2019) highlights the importance of digitalization and home automation in this context. Energy efficiency is another crucial component in this decarbonization effort, particularly significant in residential buildings, which currently account for approximately 27% of the total final energy demand across

*Abbreviations:* A2W, air to water; AI, artificial intelligence; API, application programming interface; BSP, balancing service provider; CDM, canonical data model; DHW, domestic hot water; DR, demand response; DSO, distribution system operator; EU, European Union; EV, electric vehicle; HEMS, home energy management system; IoT, Internet of things; IT, information technology; LA, lead-acid; LSTM, long short-term memory; ODP, ontology design pattern; PV, photovoltaic; R&D, research and development; SME, small and medium-sized enterprise; TSO, transmission system operator; VPP, virtual power plant; (V)RES, (Variable) Renewable energy source

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the EU-28 countries (Eurostat, 2024). Most of the housing stock that will exist in 2050 has already been built and will require renovation. These renovations should include a shift towards sustainable thermal systems, employing efficient products and appliances.

Integrated variable renewable energy sources (VRES or simply RES), coupled with storage systems and appropriate control capabilities, play a pivotal role in guiding European economies towards the desired climate neutrality. Their incorporation in contemporary energy systems is often mentioned as another key prerequisite to achieving sustainability goals. However, the reduction of the power system's inertial capabilities is a known drawback of grids with high renewable penetration as reflected in the frequency response (Alqahtani et al., 2023). As opposed to traditional power supply systems that rely on large-scale base generators in the form of thermal or nuclear coupled with plants with a shorter response time like hydro and gas power plants, systems with a high degree of inverter-fed RES power simply have a lower flexibility to react to abrupt disturbances. As noted in Hoke et al. (2021), existing methods for fault detection and protection are adapted to typical behavior which is expected from synchronous machinery, and not inverter-based power generators with complex control dynamics.

A particular challenge for RES penetration in European grids is posed by island use cases as their energy systems, owing to their remote geographical position, are often placed in a precarious position in which the balance between supply and demand can be easily disturbed (Jelić et al., 2020). In islands, the need to achieve self-sustainability in energy communities is greater than with connected systems. These microgrids are energy-vulnerable and are among the most in need of transitioning from their current reliance on fossil fuels to RES-based systems. Islands face the additional challenge of limited access to other energy networks, often depending on more costly and environmentally detrimental fossil fuels that must be imported for their energy production. This combination of isolation from larger power systems and reliance on imported fuels makes islands unable to trust in their energy supply. The clean energy transition for islands depends on increasing the penetration of RES into the local electricity grid. In this regard, energy storage plays a crucial role by facilitating the flexibility of energy production from RES, leading to a more efficient integration into the grid. In the context of a microgrid on an island, characterized by small networks of pure electricity users or prosumers that sometimes rely on their connection to a centralized grid, these systems encounter additional operational challenges. These challenges are typically attributed to their remote locations and the lack of sufficient maintenance infrastructure and support which further affects the ability to promptly address adversities in the electrical system. Furthermore, additional operational issues may arise in the event of a loss of connectivity with the mainland.

Investigating an island's current energy system is crucial for understanding its dynamics, as a thorough analysis of energy production and consumption informs the priorities for transitioning to clean energy, with the scope of this description depending on available resources and data to effectively guide the island's transition (Montero Carrero et al., 2022). Energy poverty is a complex problem that requires detailed analysis to identify its causes, with one of the most common being low household energy efficiency (European Commission and Energy Poverty Advisory Hub, 2022). By applying these strategies, islands can not only lower final consumer electricity bills but also achieve lower levels of energy poverty through energy efficiency measures.

Specifically, the increase in RES penetration adds complexity to the challenges faced by distribution system operators (DSOs) tasked with managing microgrids. Islanders often hesitate to retrofit their households and update their thermal systems to new ones that solely rely on electricity. This hesitation is mainly due to the lack of grid reliability, which causes electrical energy shortages and remains a significant challenge for users. The unreliability affects the dependability of electrical appliances, thereby making the transition to more efficient thermal systems, such as heat pumps, difficult since these systems rely solely on the electrical grid. This aspect is particularly important as heating and cooling systems account for about 50% of the EU's energy consumption, with only 23% of the energy used in the residential sector coming from renewable sources in 2020 (European Commission et al., 2023).

In the context of smart microgrids, the listed challenges not only impact system reliability but also affect the collection of data crucial for maintenance and decision-making processes. The limited number of consumers and the geographical distance from the mainland contribute to potential challenges with internet connectivity in these isolated areas. Islanders face significant obstacles in adopting and maintaining renewable energy systems due to a shortage of skilled technicians and contractors, compounded by geographical isolation that complicates system maintenance and repair, ultimately affecting reliability, energy autonomy, and residents' willingness to transition (Tellarini and Gram-Hanssen, 2024). When focusing on clean energy transitions, energy communities empower individual consumers to actively participate by providing flexibility services, generating, consuming, sharing, or selling electricity through demand response (DR) and storage systems, while also enhancing public acceptance of renewable energy projects, particularly in small municipalities and communities (European Commission and Directorate-General for Energy, 2024). Such characteristics enable final consumers to contribute to the flexibility provided to energy grids. By focusing on increasing energy self-consumption within communities, energy transmission losses are minimized and the integration of RES is supported.

Finally, the transition towards sustainable systems can be gradual and, due to costs but also varying availability and other reasons, often results in a mixture of assets from different manufacturers being installed in prosumers' premises. By extension, all of these devices identify using a distinct set of parameters, utilize different protocols, messaging formats, and control message structures. This heterogeneity presents a notable challenge for non-proprietary solutions that aim to transcend closed single-vendor systems and include different equipment providers. Ensuring interoperability and harmonizing a diverse ecosystem of energy assets is another challenge that should be given due consideration as adequate addressing is needed for any analytical app to be able to interface with the on-site equipment and result in the desired efficiency benefits.

Considering the challenges of RES integration and interoperability, especially in island energy systems, this paper outlines the development, implementation, and use of an integrated cloud platform for community energy management. The platform offers benefits to both energy end-users and aggregators or service providers by enabling efficient energy management. Alongside these processes, the paper includes a selection of results and considerations from the EU's Horizon 2020 REACT project that served as the primary context for the development of the aforementioned cloud platform. The project's implementation took place on three pilot islands with unique energy systems and requirements: La Graciosa in Spain, San Pietro in Italy, and Aran Islands - Inis Mór in Ireland. Each island was selected to represent different climatic zones and demographic profiles, enabling a comprehensive evaluation of the REACT solutions which included various novel technologies intended for bolstering self-sufficiency and reducing reliance on polluting energy sources. With the primary focus on providing positive contributions to the energy balance of geographical islands, the provided discussion focuses on the technical aspects of the proposed cloud platform and the repercussions of its use on key variables used to monitor energy use. While improvements to energy self-sufficiency have direct consequences on financial sustainability, these aspects are further explored in the context of decarbonization platforms in related publications such as Barney et al. (2021) and Barney et al. (2022).

The remaining part of the paper is organized as follows. Section 2 presents an overview of the state of the art in terms of scope and features of various energy management platforms and approaches with an in-depth analysis of different battery technologies which were a key consideration within the REACT project. Section 3 presents the structure of the proposed platform in terms of IT infrastructure followed by Section 4 which depicts a set of services, some based on machine learning methods, which augment this platform and aim to provide suggestions and setpoints for devices and end users to apply in order to maximize self-sufficiency. Section 5 provides a selection of applications of the platform in both electric and thermal domains with Section 6 providing a summary, concluding remarks, and future research outlook.

## 2. State of the art

In order to provide further context for the subsequent platform presentation, the following paragraphs provide an analysis of different considered aspects, application scopes, and utilized techniques in a selection of energy management approaches that were considered related to the approach that was intended to be utilized within the platform. In addition, a study of market readiness with a comprehensive parametric comparative analysis for suitability of different battery technology utilization in island energy systems is also presented.

### *2.1. Energy management approaches*

Several comprehensive energy management approaches could be combined to monitor and control renewable energy technologies, storage systems, and dispatchable loads, such as virtual power plants (VPPs), smart grid technologies, smart metering systems, and home energy management systems (HEMS). Facilitating these approaches in a digital platform enables improved energy efficiency and cost savings through optimal load management and flexibility. Multiple commercial solutions combine various energy management approaches targeting diverse users. The following paragraphs highlight features from leading solutions that incorporate energy management services via digital platforms, focusing on VPPs and DR with a summary of the designated types of users given in Table 1.

In their platform Virtual Power Plant and Smart Home Management System (tiko Energy, 2024), Tiko Energy Solutions integrates a VPP with a HEMS to link residential and small and medium-sized enterprise (SME) assets. The energy management system and the app link residential devices regardless of their models and connect them in one place. This helps end-users manage their energy consumption more efficiently and save money. The devices are connected to a VPP, which yields additional revenue through flexibility.

Siemens's VIBECO (Virtual Buildings Ecosystem) (Siemens, 2024) VPP software platform intelligently balances electrical loads from buildings connected in a microgrid, incorporating renewable energy and energy storage. The VPP consists of a digitized DR system, which makes it possible to combine the small electrical loads of buildings or industrial sites so that building operators can sell energy back to the reserve market, leading to increased electricity market flexibility.

EPQ's Energy Service Solution (EPQ, 2024) aggregates consumption, generation, and storage resources by offering flexibility to national and local grid operators. EPQ acts as a balancing service provider (BSP) – an aggregator providing balancing services to the transmission system operator (TSO). The BSP aggregates prosumers, enabling consumption and production units and storage systems to participate in the ancillary services market and offering flexibility. EPQ's interruptible loads program aims to secure the functioning of the national electricity system if resources procured on the market are insufficient. This program generally involves large industrial customers with a severe implication of electricity cost on their production cost, and that can interrupt or shift production cycles in case of need.

Voltalis's DR Technology Solution (Group Voltalis, 2024) enables positive contributions to the power system by smartly curtailing a building's energy consumption and avoiding using $CO_2$-emitting power plants. Their smart devices provide a solution to link flexible consumption with the power system. The technology covers all aspects of DR, including smart devices in participant buildings, dedicated HEMS for participants, and a central control room connected to power markets.

Next Kraftwerke provides a NEMOCS Solution (NEMOCS, 2024) which, using a standard interface, connects renewable energy assets and controllable loads into the VPP and remotely steers them. The control system displays and records real-time information on current capacity, storage levels, and standby status of assets. Price signals from the energy markets and control signals from the system operator are processed in seconds and converted to operational commands for the assets. The central control system remotely manages each asset and ensures the predetermined schedule is executed respecting individual restrictions.

The Real Time Operational Smart Grid for Europe (ROSE) smart energy platform by MAPS S.p.A. Maps Energy (2024) facilitates value creation for the energy industry by deploying renewable plants and implementing efficient energy management and distribution. This platform integrates technological advancements with a strong emphasis on market innovation. It includes a cloud-based ROSE energy community application for simulating and managing local renewable energy production and sharing among private citizens, businesses, and municipalities. This comprehensive solution comprises an intelligent energy management module and a mobile app to engage participants and recommend real-time beneficial practices.

The Regalgrid (Regalgrid, 2024) innovative platform by Regalgrid Europe comprises real-time energy services, aggregation, and sharing. Using its smart node control unit, a bidirectional gateway that connects to the photovoltaic system devices with or without a storage system, the Regalgrid platform transforms consumers into advanced prosumers. It brings them into an energy community where exchanging energy, managing consumption directly, and establishing a direct relationship with installers and energy providers is possible. Advanced service providers can handle this aggregation of users with a licensing agreement in line with the objectives the EU has set down in terms of smart communities. Regalgrid can offer its services to communities of private prosumers, utilities, and network managers by supplying turnkey solutions.

GridPilot (AYESA, 2024) from Ayesa Advanced Technologies is designed to monitor and manage the energy utilization from new generation systems, enabling the sale of excess electricity back to the grid using artificial intelligence (AI) algorithms. GridPilot can autonomously determine the optimal times for storing, using, or selling electricity, thereby preventing grid overload. The system utilizes a VPP to consolidate various energy resources, including solar panels, stationary batteries, and electric vehicle (EV) batteries commonly found in homes, businesses, and factories. It then autonomously determines the optimal times for energy storage, consumption, or selling, all while ensuring safety and control through AI and internet of things (IoT) technologies, which are crucial for market operations.

CyberNOC (Toshiba, 2024) by CyberGrid (Toshiba) is a modular and scalable system that acts as an economic optimizer for flexible energy demand management, allowing the creation of advanced DR schemes in near real-time mode. It provides seamless and secure flexibility aggregation and monetization on different electricity markets (ancillary services, balancing, intraday, day-ahead, etc.). It can be used by network operators and retailers and implemented in smart city solutions. Scalable technology pools flexible energy resources into a VPP, connecting flexibility providers to the various layers of energy markets (retailers, traders, prosumers, DSO, TSO). With its embedded control tools, smart metering, microgrid management solutions, and various other grid services, CyberNOC auto-manages and optimizes distributed flexibilities. The software system operates on two-second intervals for system communications.

Overall, the solutions listed in Table 1 optimize energy consumption, integrate renewable sources, and enhance grid flexibility. Their platforms enable efficient management of residential, SME, and industrial assets, allowing participation in energy markets and contributing positively to grid stability.

**Table 1**
Overview of user classification for the energy management solutions discussed in this study, indicating the types of end-users each solution is designed to focus on.

| | Residential | Industrial | Commercial | Aggregators | SMEs | DSO and TSOs | Utilities | Energy traders | Large businesses | Govt. and int. organizations |
|---|---|---|---|---|---|---|---|---|---|---|
| Tiko Energy | + | | | | + | | | | | |
| Siemens VIBECO | + | + | + | | | | | | | |
| EPQ Energy Service | | + | + | | | + | | | | |
| Voltalis DR Technology | + | + | + | | | | | | | |
| NEMOCS Solution | | | | + | | + | + | + | | |
| ROSE Smart Energy | + | + | + | | | | | | | |
| Regalgrid | + | | | | | + | + | | | |
| GridPilot | | | | | | | | | + | |
| CyberNoc | | | | + | | + | | | | + |

The proposed platform leverages its unique role as an intermediary between island residents (as energy users and flexibility providers) and energy service providers, aggregators, and community managers. By harnessing the full potential of available energy infrastructure, it delivers proactive, optimized energy management based on predictions of production, consumption, and storage availability. The novelty of the proposed approach lies not only in its high interoperability achieved through a cluster of diverse database and semantic technologies, but also in its autonomous optimal energy management capability. This is enabled by a unique control loop that integrates forecasting and optimization services with specialized control adapters. The design of the proposed platform was created with interoperability as one of the main requirements. Unlike commercial solutions which are often vendor-specific or require uniform hardware ecosystems, the proposed platform allows integration by relying on semantic and syntactic interoperability while also providing multi-protocol support. Semantic interoperability is achieved by utilizing a semantic repository based on a custom ontology which ensures that data from different sources are uniformly described and interoperable at a semantic level while syntactic interoperability is obtained by making use of a canonical data model which enables uniform message exchange between data sources and the platform. Regarding field-level communication protocols, owing to the utilization of a combination of light-weight and industry standard protocols such as MQTT and Modbus, as well as the implementation of several custom-built API adapters, the platform enables integration with a wide variety of devices.

As a result, the proposed platform brings increased RES hosting capacity and reduces reliance on the grid through the integration of intelligent implicit and explicit demand response strategies if needed, reducing costs for all stakeholders. A key aspect also taken into consideration in the platform design process was engaging end consumers in energy management, demonstrating effectiveness through pilot projects on diverse islands, and developing business models for large-scale replication.

### *2.2. Storage technologies*

A self-sustainable renewable-powered island community can benefit from storage systems providing various services such as improved frequency responses, frequency containment reserves, frequency restoration reserves, and energy shifting (Ralon et al., 2017). While compressed air energy storage is unsuitable for islands because of their size and complexity, hydropower is the best solution mainly because of its low cost. The impact amplifies with hybrid pumped hydro storage and a battery storage system. However, when pumped hydro storage is unavailable, battery technology offers the best solution for island storage. According to a recent report by the EU's Joint Research Centre, the ongoing research and development in battery technologies commit to performance enhancement, durability improvement, increased safety, and cost-minimization (Bielewski et al., 2022). The growing adoption of emerging alternatives like lithium-ion (Li-ion) and sodium-ion (Na-ion) batteries has complemented conventional lead–acid (LA) and nickel (Ni) battery advancements. Furthermore, comparatively cheaper, and more sustainable flow batteries are being developed in response to the increasing demand for long-term storage. Despite initially penetrating the market at a higher cost than conventional solutions, these emerging technologies offer improved functionalities, typically targeting high-end or niche markets. Li-ion technologies are gaining significant traction in stationary and transport applications. Extensive research and screening efforts are going on to encompass improvements in existing technologies and explore novel chemistries, aiming for commercialization and widespread adoption. In summary, Table 2 compares the key performance metrics of different battery technologies based on a collection of relevant sources while Fig. 1 shows the commercial stages of the battery technologies of Table 2 broadly divided into three categories (Mandal et al., 2022):

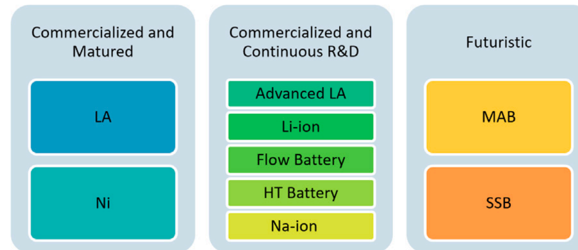


**Fig. 1.** Commercial development stages of selected battery technologies, highlighting those that are fully commercialized, under continuous R&D, or considered futuristic. *Source:* Adapted from Mandal et al. (2022).

(i) commercialized and matured,
(ii) commercialized and continuous R&D and
(iii) futuristic (under R&D/limited commercialization).

Self-sustainable and smart renewable energy communities should also consider additional criteria for storage systems:

(i) communication, integration, and interoperability,
(ii) technical innovation,
(iii) market readiness,
(iv) environmental impact and
(v) cost of storage.

Based on the technical performance metrics and the additional criteria, the commercialized matured and continuous R&D batteries for community storage have been benchmarked in Table 3. Based on the benchmarking, lithium-ion technology is the most suitable candidate for island energy storage, followed by sodium-ion and advanced lead–acid (lead-carbon) batteries. Flow and nickel batteries are the subsequent preferred alternative technologies. However, regardless of the technology that is ultimately to be integrated, the proposed platform was designed to support various types of batteries without limitations pertaining to the types of control actions that they need to perform.

## 3. Energy management platform

The approach presented in this paper effectively leans on the co-operation of a set of smart services discussed in the next section and solutions based on information technology that aim at extending the base functionality that is generally provided with the RES equipment

**Table 2**
Overview of key technical performance metrics for the battery technologies discussed in this study, including energy and power density, cycle life, roundtrip efficiency, and charge/discharge rates. Mandal et al. (2022), Taibi et al. (2020), Sánchez-Díez et al. (2021), Aquino et al. (2017), Durmus et al. (2020), Li et al. (2023), Salado and Lizundia (2022), Luo et al. (2021), Ye and Li (2021), Randau et al. (2020), Natron Energy, Inc. (2023), Victron Energy (2023), Sharmoukh (2025), Sumitomo Electric (2025), Adeyemo and Tedeschi (2023), Olabi et al. (2021), Riley (2024).

| Battery technology | | Energy density [Wh/kg] | Power density [W/kg] | Cycle life [cycle] | Roundtrip eff. [%] | C-rate [C] |
|---|---|---|---|---|---|---|
| Lead acid (LA) | LA | 30–50 | 30–50 | 500–1000 | 79–90 | 0.05–0.20 |
| | Adv. LA | 30–50 | 180 | 2500–4500 | 79–90 | 0.05–0.20 |
| Lithium-ion (Li-ion) | LFP | 90–120 | 4000–6500 | 1000–2000 | 85–95 | 1 (Typical) |
| | NMC | 150–220 | | 1000–2000 | | 0.7–1.0 |
| | LCO | 150–200 | | 500–1000 | | 0.7–1.0 |
| | NCA | 200–260 | | 500 | | 0.7–1.0 |
| | LMO | 100–150 | | 300–700 | | 0.7–1.0 |
| | LTO | 70–80 | | 3000–7000 | | 1 (Typical) |
| Flow batteries | VRB | 20–70 Wh/l | 0.5–2.0 W/l | No limits | 60–85 | 0.25–1.00 |
| | ZnBr | 60–85 | 0.5–2.0 | | | 0.125–0.250 |
| High temperature (HT) | NaS | 150 | 120–160 | 4500 | 70–90 | 0.167 |
| | NaNiCl2 | 90–120 | | 2000 | | |
| Nickel (Ni) | NiCd | 45–80 | 150 | 2000 | 70 | 1 |
| | NiMH | 60–120 | 250–1000 | 700–1000 | 66–92 | 0.5 |
| Metal-Air batteries | MAB | 50–1700 | 100 | >1000 | <60 | 1 |
| Solid state batteries | SSB | >1000 | 374.7 | 10 000 | 90 | 0.2–100.0 |
| Sodium-ion | Na-ion | 130–160 | 1000 | 6000 | 92 | 0.1–2.0 |

**Table 3**
Benchmark comparison of commercial battery technologies for community energy systems, based on subjective scoring from A (best) to C (worst) across key criteria including technical performance, communication and interoperability, innovation, market readiness, environmental impact, and costs.

| Benchmark criteria | LA | Ni | Advanced LA (PbC) | Li-ion | Flow | HT | Na-ion |
|---|---|---|---|---|---|---|---|
| Technical performance | B | A | A | A | A | A | B |
| Communication, integration and interoperability | C | A | A | A | A | B | A |
| Technical innovation | B | B | B | A | B | B | B |
| Market readiness | A | A | A | A | B | B | A |
| Environmental impact | C | C | B | A | A | B | A |
| Costs | A | B | B | B | C | C | B |

that island communities use to improve their self-sufficiency. The platform architecture, shown in Fig. 2, can be grouped into several groups of components:

- Data repositories;
- Services (forecasting, optimization, etc.);
- Adapters to the external systems and APIs;
- Database middleware;
- Field level devices;

The platform receives inputs from various field-level devices, including controllable ones such as heat pumps, photovoltaic (PV) systems, batteries, fuel cells, electrolyzers, and smart meters. These measurements are collected via manufacturer application programming interfaces (APIs) or energy gateways and stored in the timeseries database for further processing. Forecasting services then utilize these measurements, along with weather data, to generate production and consumption forecasts.

With the forecast and measurements as inputs, central optimization algorithms can create optimal power and thermal curves for all relevant energy assets. These curves are transformed into control signals (so called "control actions"). Subsequently, these control actions are distributed to the edge devices via respective cloud interfaces or forwarded directly to the controllable assets. A feedback channel is implemented via the measurements that are read from the sensors.

The services for running the platform require bulk access to measurement, forecast, and other data, which is enabled through direct database access. For the field-facing APIs and middleware (MELCloud API, OpenMUC Edge Gateway, and MIDAC API which partially run on field-level devices), a more robust, bandwidth-efficient communication method, is required and implemented.

### 3.1. Edge device communication protocols

One of the main requirements for the proposed integrated cloud platform was to enable integration with diverse devices and data sources available at the pilots at the field level. Since these devices use different communication protocols and data formats, a common data collection and control protocol was created to facilitate data exchange.

MQTT was selected as the base communication protocol due to its open-source nature and suitability for embedded communication, given its lightweight design, asynchronous communication, scalability in many-to-many communication, wide availability, and ease of implementation. A central MQTT broker (server) has been set up as the foundation for all subsequent communication. Communication is executed via the broker and organized into topics. Each participant can send or, using the domain-specific terminology, "publish" messages or subscribe to topics to receive all messages published to that particular topic. In this way, entities can communicate while only the broker needs to be publicly accessible on the network, a significant advantage as it simplifies network setup.

Communication was naturally segmented into transmitting measurements and receiving control signals. Measurements for each gateway are transmitted collectively on a single topic, while dedicated control signals are assigned on a per-device basis, reducing traffic on the edge devices. Additionally, a request-and-response channel is used to confirm whether the operation can be successfully executed or forwarded to the actuator.

To integrate the MQTT protocol into the platform, which operates with data stored in databases, middle-ware is used: the Database Adapter and OpenMUC Orchestrator (gray components in Fig. 2). The

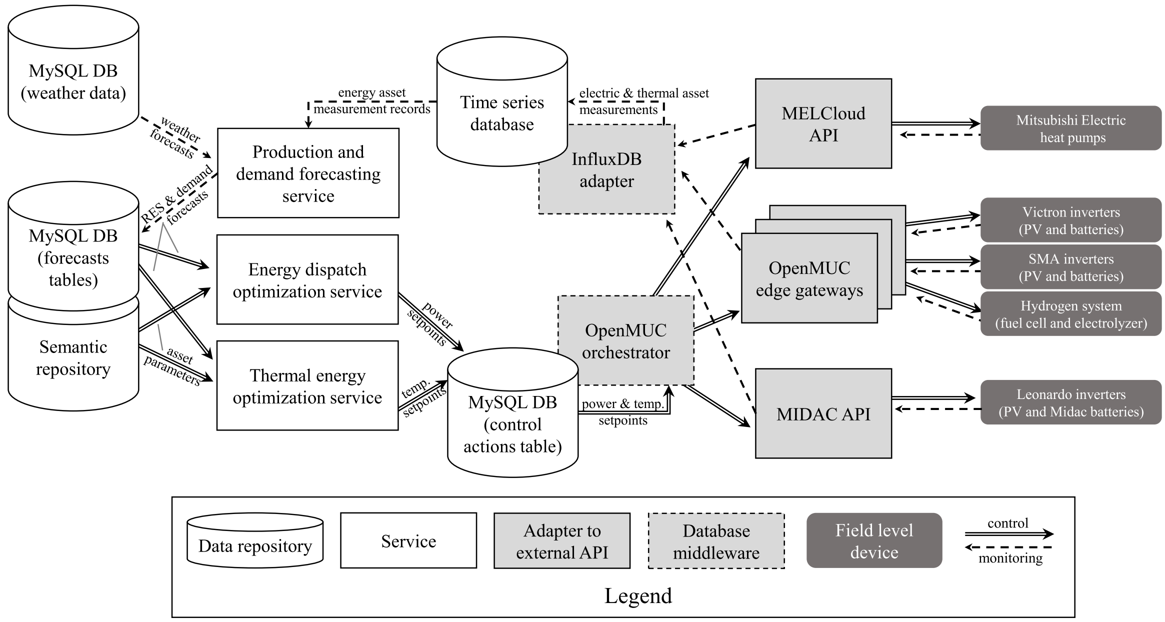


**Fig. 2.** Overview of the proposed platform architecture for integrated energy management, illustrating the interaction between data repositories, optimization services, middleware components, external APIs, and field-level devices for control and monitoring.

Database Adapter receives all measurements and stores them in the measurements database. The OpenMUC Orchestrator reads the control actions from the database, distributes them to the designated channels, and also stores the device responses in the database.

### 3.2. Field level interfacing

Various field-level devices were integrated into the platform, some with the purpose of providing data, and others with the capability to also receive control actions. These assets were interfaced through different communication protocols and middleware. The following subsections detail the specific interfacing methods used to connect these assets to the platform.

#### 3.2.1. OpenMUC energy gateway

Most actuators were integrated using the OpenMUC, a versatile Java framework designed for implementing individual monitoring and control applications. The interfacing with the actuators and meters was implemented using Modbus communication, with individual interfaces supporting each actuator. By extension, the platform offers the capability of collecting and storing data from assets connected to these actuators like battery storage and PVs for electrical inverter-based systems, EV chargers, and accompanying electrolyzer and fuel cells for hydrogen systems. An exemplary set of primary targeted and supported actuators included inverters and PLCs.

The OpenMUC framework was used to transmit sensor measurements and execute control actions via interfaces, using for example the built-in MQTT and Modbus libraries (Mittelsdorf, 2024). Manufacturer-specific configurations and communication protocols were implemented on the platform, utilizing predefined controls while adding more advanced control modes. Based on the use cases that involved modifying predefined power draw values, diverse control modes were implemented to manipulate storage charge and discharge rates in order to achieve one of the predefined targets:

- Maintain an active power setpoint at connection points between energy assets;
- Maintain an active power setpoint at the grid connection point;
- Generation power shaving, i.e., limitation of feeding into the grid exceeding a specific value;
- Consumption power shaving, i.e., limitation of drawing from the grid exceeding a specific value;

with the complete list of the implemented modes available in Maruf et al. (2022).

Since the OpenMUC Energy Gateways operated on remote islands with potential internet connectivity interruptions, a fallback mechanism was implemented to ensure control actions could still reach assets if primary delivery failed. This mechanism defaulted to an active power setpoint of zero at the grid connection point, maximizing self-consumption which is effectively the same behavior exhibited by the installations in the baseline scenario discussed later. While the cloud platform's service stack forms the core of the proposed asset management, this presents an additional redundancy layer. If the cloud control loop fails or connectivity is lost, the system switches to isolated operation using fixed if-then rules, maintaining near self-sufficiency for the current time step. Unlike the platform's optimized control loop which leverages forecasting and smart planning over longer horizons, this backup approach prioritizes immediate resilience. During occasional disruptions, the backup algorithm proved effective in sustaining device operation until platform connectivity was restored.

#### 3.2.2. MELCloud API

Mitsubishi Electric heat pumps, including air-to-water and air-to-air systems, connect to the MELCloud platform via Wi-Fi connection. MELCloud allows users to monitor and control heat pump settings through a web interface, with integration into the proposed platform using a specific API. The MELCloud bridge translates data and commands between the proposed platform's canonical data model (CDM) format and the proprietary MELCloud API. During setup, MELCloud bridge authorizes each user with MELCloud, and stores authentication tokens in a MySQL database. MELCloud bridge periodically queries MELCloud for heat pump data, transforming it to CDM format for use by the proposed platform. Control action requests (e.g. temperature setpoint) from the platform are sent via MQTT to the MELCloud bridge, translated, and executed through the MELCloud API, with control responses similarly sent back to the platform. Additional detailed information is available in Freeman et al. (2024).

#### 3.2.3. MIDAC API

The MIDAC Data Bridge integrates MIDAC batteries with the cloud platform using MQTT protocol. In particular, it translates data between the proprietary MIDAC format and the CDM format. Battery devices send real-time energy measurements and event notifications, which are converted into JSON CDM messages and published to the MQTT Broker. On the other hand, control requests (e.g. charge/discharge battery) are processed and sent to the battery devices, where the command responses are relayed to the platform. The system uses a Mosquitto MQTT broker and NodeRED for processing.

### 3.3. Data repositories

Another key element of the IT infrastructure provided by the cloud platform is the cluster of database technologies that are hosted within it. Due to the complexity of managing the entire energy system, different data types must be processed to provide an efficient means of system management.

#### 3.3.1. Time-series database

For the measurements database, a database specialized for storing time-series data is a suitable choice. An instance of InfluxDB was selected because it integrates well with various frameworks and is included out of the box as part of the Telegraf-InfluxDB-Chronograph-Kapacitor package, also known as the TICK stack, which allows easy integration and provides a graphical user interface. Additionally, these databases are designed to manage large volumes of data generated over time and support high-speed, efficient querying and analysis, particularly when specialized functions need to be applied to large datasets.

#### 3.3.2. MySQL database

MySQL is used in the proposed platform primarily for data exchange between services. Specifically, as the services run sequentially, each service stores its results in MySQL, allowing subsequent services to read and utilize the data. This is particularly important for the later verification and validation of the results provided by the analytical services. All types of forecasts, setpoints suggested by the optimization services for electric or thermal assets, and all control actions were persisted in a MySQL database for this reason.

#### 3.3.3. Semantic repository

One of the main challenges in smart grid interoperability is the collection of information from heterogeneous sources, which vary in data structures, semantics, and software or hardware platforms. Making this information uniformly accessible is essential for leveraging its value in a DR platform. To address this, a common vocabulary was established through an appropriate ontology. This ontology forms a semantic layer on top of raw data, providing essential knowledge for services like forecasting, optimization, and visualization tools to function. By representing data through ontologies, the solution achieves interoperability at a semantic level and ensures clear, unambiguous data sharing between parties. The development of this ontology followed the linked open terms methodology (Poveda-Villalón et al., 2022), which includes requirements specification, implementation, publication, and maintenance.

The requirements specification process defines why the ontology is being developed and outlines its needs. A group of end users, domain specialists, and ontology engineers create competency questions to guide the design, such as "*What are the qualities observed by a given piece of equipment?*" or "*What is the gateway of a given installation?*". During implementation, the ontology is built modularly, using a formal language and reusing existing ontologies where possible. Well-known ontology design patterns (ODPs) and ontologies were selected and partially reused to meet the specified requirements:

The core of the developed ontology is based on the Execution-Executor-Procedure (EEP) Ontology Design Pattern (ODP) (Esnaola-Gonzalez, 2024), which supports the description of sensors and devices that monitor or control features within a space. On top of this foundation, additional elements such as categories (classes), specific examples (individuals), and the relationships between them were built to meet the need identified. To build on existing concepts, terms were reused from established ontologies. Properties indicating the manufacturer of a piece of equipment were adopted from SAREF (Smart Appliances REFerence) (European Telecommunications Standards Institute, 2024) while classes describing the structure of buildings and links between spaces and equipment were used from the Building Topology Ontology (BOT) (Rasmussen et al., 2017). Also, sensor readings and their corresponding units of measurement were connected using concepts from QUDT (Quantities, Units, Dimensions, and Data Types) (QUDT.org, 2024). This reuse of existing ontologies helped to ensure compatibility with other systems and made the data easier to understand and integrate. Once completed, the ontology was validated using Themis (THEMIS, 2024), and its design correctness was evaluated with the Ontology Pitfall Scanner (OOPS!) (Ontology Engineering Group, 2024a) tool, producing satisfactory results. An overview of the final ontology is shown in Fig. 3.

The information needed to populate the ontology was collected by pilot case coordinators using spreadsheets called data point lists. The transformation from these data point lists to the ontology instantiation was automated using a service based on the Apache Jena framework. This service extracted the information from the spreadsheets, annotated it semantically with the appropriate ontology terms, and stored it in a resource description framework store built using OpenLink Virtuoso, where it remained accessible along with the ontology, forming the developed semantic repository. The publication process ensured that the ontology was available in both human-readable documentation and machine-readable format via its uniform resource identifier. Finally, the maintenance phase ensured that the ontology was updated when new requirements arose or issues with misplaced data or inconsistent data formatting were identified. The developed ontology, with complete documentation, was published in the repositories on w3id (Esnaola-Gonzalez, 2021) and Linked Open Vocabularies (Ontology Engineering Group, 2024b) repositories, and later included in the Ontology Landscape as part of the Catalogue of Ontologies for Semantic Interoperability by the Alliance for IoT and Edge Computing Innovation.

In summary, the semantic repository stores the topology of the installations at pilot sites, defining the relevant metadata associated with the installations, the installed equipment, and the data gathered by them. It also defines the relationships between the equipment in a hierarchical structure, as well as the specific data collected by each piece of equipment, including relevant attributes. Some of these attributes were also related to the CDM defined in the platform, which served as the common message format to ensure syntactic interoperability of the data exchanged between the field and the cloud components. Additionally, the semantic repository stores the necessary links to map the installations to the time-series database, responsible for storing the raw data collected from the field-level equipment. It is worth mentioning that the application of the ontology in the workflow has not introduced any critical latency in the process of control action derivation. This can be concluded based on the fact that each query only takes up several seconds to get all necessary parameters for a given Island and that this process is run only per optimization cycle, i.e., only once every few hours depending on the optimization schedule.

## 4. Energy management services

The previously depicted IT framework provides the backbone of the integrated cloud platform proposed and is intended to serve as the foundation for the set of energy management services developed on top.

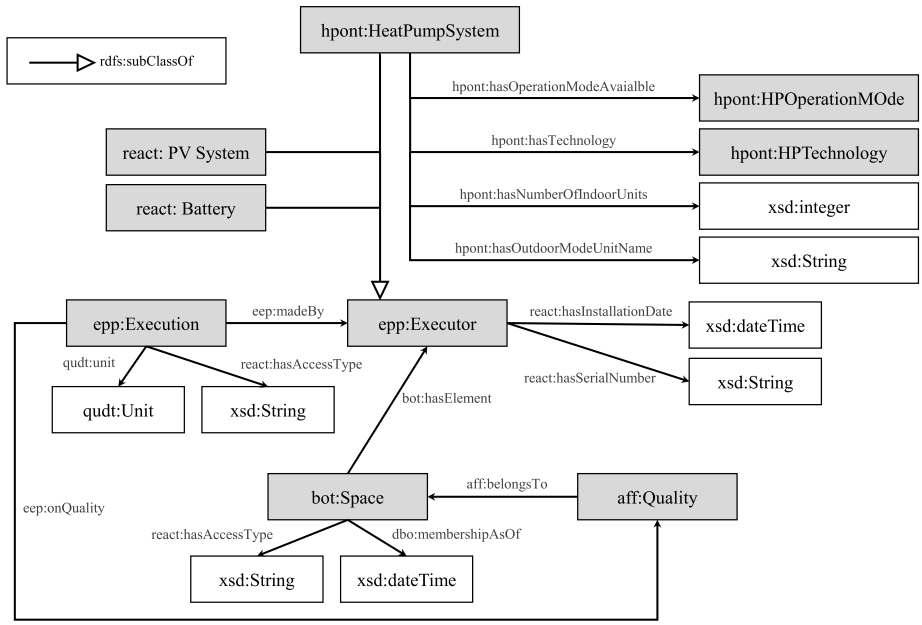


**Fig. 3.** Excerpt from the developed ontology, illustrating key classes and relationships used to represent heat pump systems, energy devices, execution processes, and related contextual data.

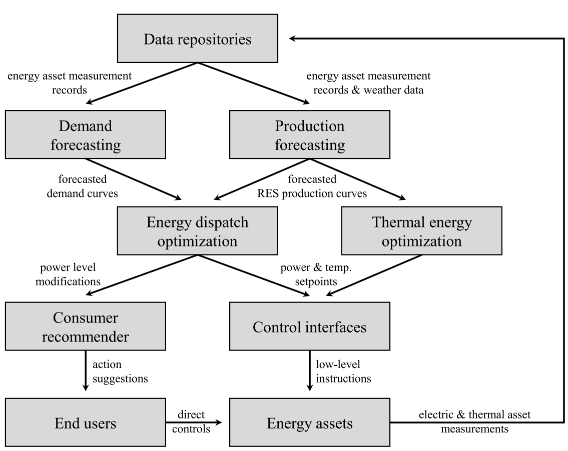


**Fig. 4.** Generalized representation of the measure-forecast-optimize control loop, illustrating the flow of information between data repositories, forecasting modules, optimization services, control interfaces, and end-user or asset-level components.

Each one of these services, as individual software components, serves a particular role in the forecast-optimize-control loop, depicted in Fig. 4. When operating in unison, this set of services aims to make the most use of available energy infrastructure and the collected data, and suggest the optimum course of action in terms of energy asset management through the provision of optimum profiles. By implementing data-driven machine learning methods for predicting energy availability and energy consumption as well as modeling and optimization methods, this loop intends to bridge the gap between underutilized energy infrastructures and self-sufficient communities.

### *4.1. RES production forecasting*

As already established, the main goal of the energy management service cluster is to derive the optimal set of control actions for energy assets through the establishment of the optimum profile. In order to perform this process, two prerequisites need to be met. The first is to establish an estimation of the amount of renewable energy that is expected to be generated by locally available RES, specifically PV panels in the cases of the discussed pilot sites. The second, to be explored in the following subsection, is estimating the expected aggregate amount of energy consumption by various appliances within each facility. Regarding the former aspect, since physical parameters of the installed PV plants were not available at the time of development, and with data-driven models showing excellent performance in terms of precision and accuracy, machine learning-based approaches were selected for application for the cloud platform.

The methodology selected for the production forecaster service is initially inspired by Theocharides et al. (2017) where the authors opted to implement an approach based on ensemble neural networks. This methodology was further enhanced for the development of the proposed platform with the application of a more complex hybrid long short-term memory (LSTM) architecture as described in more detail in Pujić and Tomašević (2021). In order to substantiate the improvement in the obtained results, the performance of the achieved estimations was compared against the state-of-the-art approach using an ensemble of artificial neural networks. In order to provide a meaningful comparative analysis, three different model structures or varying complexity were trained using real-world data from the islands for which they would be ultimately applied to and designed to have meteorological conditions as the inputs while providing estimated PV production as the output. The initial approach was an ensembling method with a simple ANN, which is, owing to the use of ensembling, already one step above what would be considered a basic approach. The second approach is a single hybrid neural network with its architecture presented in Table 4 as proposed by Wang et al. (2019). This architecture includes the addition of LSTM layers, making the network more suitable to operate on sequential time series data such is the case in the discussed application as well as the addition of convolutional layers for improved feature extraction. Finally, in an attempt to further improve predictive performances, an ensembling hybrid model is created by combining the aforementioned two approaches, resulting in a model as described in Pujić and Tomašević (2021).

After training all the analyzed models and optimizing the number of weak learners for ensembling models, the accuracy of obtained forecasts can be compared. The initial approach achieves a RMSE of 3.58 kW when evaluated on a test data subset obtained from a reference PV plant in the Adeje town on Tenerife Island with a capacity of 40 kWp.

**Table 4**
Layer-by-layer structure of the hybrid neural network architecture used for PV renewable generation forecasting, detailing the type of layers, number of neurons or filters, filter sizes, activation functions, and dropout factor.

| Layer type | # neurons or filters | Filter size | Activation function | Factor |
|---|---|---|---|---|
| LSTM | 64 | – | tansig | – |
| LSTM | 128 | – | tansig | – |
| Convolutional | 64 | 3 | linear | – |
| Max Pooling | – | 2 | – | – |
| Convolutional | 128 | 3 | relu | – |
| Max Pooling | – | 2 | – | – |
| Dropout | – | – | – | 0.1 |
| Dense | 2048 | – | relu | – |
| Dense | 1024 | – | relu | – |
| Dense | 1 | – | linear | – |

This metric is improved upon first by the utilization of a hybrid NN in the second mentioned approach resulting in a RMSE of 3.49 kW. However, further improvements were proven possible by the ultimately utilized hybrid ensample approach which achieved a RMSE of 3.43 kW on the same test data subset. This reduction of the RMSE by 0.15 kW in absolute terms corresponds to a relative improvement of approximately 4.2 % upon the initial achieved error of the ensemble ANN approach.

Following the verification of the proposed forecasting model, the utilization of the RES production forecasting service allows the subsequent optimization service to make informed decisions on when to import and export energy from the grid as well as to guide the operation of the energy storage system. This, in turn, allows individual facilities to maximize their self-sufficiency through increased utilization of locally produced electric power.

### 4.2. Energy consumption forecasting

The second key ingredient for successfully computing the optimum energy usage profile is the forecasted curve of energy consumption, sometimes referred to as the demand or load profile. Together with the RES production forecast profile, this curve provides crucial information regarding how much energy is expected to be consumed within the facility which, in turn, is needed to match the local production with consumption as much as possible.

Due to its more stochastic nature, unlike RES production, power consumption data from appliances is, in most cases, negligibly correlated with meteorological conditions and it is difficult to find other series that can serve as good predictors. Therefore, significant efforts need to be invested in testing different approaches as well as determining which selection of predictors is the most suitable. In the absence of more suitable input variables, the ultimately selected methods often rely on previous consumption curves moderately modified depending on the type of day (working, weekend, or public holiday) and modulated in accordance with peak consumption hours.

For the purpose of determining the best methodology to use for estimating future demand profiles, several methodologies have been assessed as described in more detail in Übermasser (2021). The authors have, among others, tested a variety of approaches in different settings, including models based on polynomial interpolation, multilayer perceptron neural networks (Dudek, 2020), hybrid methodologies based on k-nearest neighbors adapted specifically to time-series analysis (Gómez-Omella et al., 2020), with the application of histogram gradient boosting regression being ultimately selected as the method of choice for demand forecasting. This method is obtained by combining features from the light gradient boosting machine (Ke et al., 2017) and methods such as XGBoost (Chen and Guestrin, 2016) resulting in a more feature rich approach. This approach has shown the potential to outperform similar methods like random forest in most cases as noted in Pedregosa et al. (2011) in a scalable way. It utilizes the distribution of input features through binning and discretization in the branching process which also aids with regularization along with support for early stopping to avoid overfitting. Another important aspect for selecting this model was its ability to handle missing data in the learning process, meaning that data gaps are not as detrimental to the final estimation quality as with other related methods. Since missing data is a particular problem in the demand forecasting scope, the selected method can be considered robust in this context. Additional details on the obtained results with this as well as other discussed approaches can be found in Übermasser (2021) with Section 5 depicting how the output is utilized in different optimization scenarios.

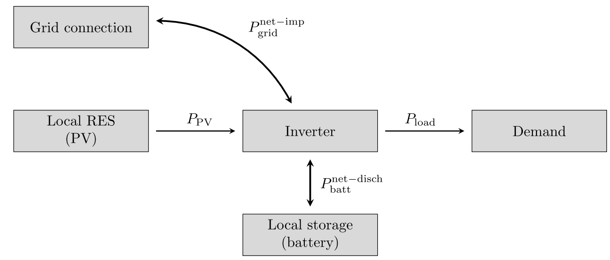


**Fig. 5.** Reference energy infrastructure model of a facility used for optimization, showing the interaction between local renewable generation, battery storage, grid connection, inverter, and demand components.

### 4.3. Energy dispatch optimization

Since the aim of this work is to provide a means of generating suggestions and control actions for individual facilities, the energy infrastructure after which the core model was developed is based around a single electrical energy bus to which different assets are connected. The generic system can import and export power from the grid while also drawing energy from local renewable sources, such as photovoltaic panels. Additionally, it includes a locally connected storage unit with bidirectional capabilities and a demand component representing the facility's energy consumption. A corresponding visual representation of this model is presented in Fig. 5.

In order to determine the adequate model formulation and, by extension, the solver selection, multiple factors were considered. First was the relatively moderate complexity of the system which, in accordance with the mentioned energy assets and the end application of this service, does not require detailed non-linear and high-order dynamics. Then, the number of facilities and the frequency at which this service needs to run to support the provision of intra-day setpoints were considered. Finally, the input error introduced by the inclusion of forecasting services as well as the selection in similar approaches within the relevant literature (Cosic et al., 2021) were acknowledged. As a result, it was determined that a (mixed-integer) linear programming approach was to be selected as a compromise between quick evaluation and complex feature support.

A particular limitation in model selection that should be mentioned for systems like the one discussed in this work is the implications that RES integration can have on the dynamics that ought to be modeled. Depending on the generation technology and based on the energy source, be it is solar, wind or another kind, each generator class has a different set of fundamental equations governing its operation and dynamic characteristics. These equations are often non-linear and may sometimes introduce a limiting factor regarding which kind of optimization procedure can be utilized. However, by strategic use of forecasting powered by machine learning models, previously recorded data and forecasted weather variables, the previously non-linear constraints governing RES operation can be converted into simple linear bounds. As such, this approach facilitates the use mixed-integer liner optimization methods and, with additional expansion of the forecasting scope, may also be applicable to other assets not considered in the infrastructure from Fig. 5.

In accordance with the defined layout and model type selection, the fundamental constraint that needs to be implemented within the energy dispatch optimization service is the power conservation law. In other words, the total energy imported, produced or sourced from storages must be balanced out with the energy exported, consumed or deposited. Assuming a reference direction towards the inverter depicted in Fig. 5, the bidirectional net power flows from the grid to the inverter, depicting simultaneously imports and exports, as well as from the battery to the inverter, simultaneously depicting charging and discharging, can be expressed as

$$(\forall t) \quad P_{\text{grid}}^{\text{net-imp}}(t) = P_{\text{grid}}^{\text{imp}}(t) - P_{\text{grid}}^{\text{exp}}(t)$$

$$(\forall t) \quad P_{\text{batt}}^{\text{net-disch}}(t) = P_{\text{batt}}^{\text{discharge}}(t) - P_{\text{batt}}^{\text{charge}}(t).$$

According to these definitions, the grid, battery and PV provide a net positive contribution to the energy balance, while the collected energy is utilized to facilitate a load curve defined by $P_{\text{load}}$. With the above-mentioned in mind, for each modeled time step $t$ the power conservation law can be written as

$$(\forall t) \quad P_{\text{load}}(t) = P_{\text{grid}}^{\text{net-imp}}(t) + \eta_{\text{inv}} P_{\text{PV}}(t) + P_{\text{batt}}^{\text{net-disch}}(t)$$

However, for variables expressed via net power flows such as the battery and grid connections, the incoming and outgoing fundamental terms should not be allowed to have nonzero values at the same time. This effect can be achieved by utilizing a set of binary (indicator) variables $y_i \in \{0,1\}$ that are linked to each term by applying the following set of constraints (assuming the grid variables for demonstration)

$$(\forall t) \quad P_{\text{grid}}^{\text{imp}}(t) \leq M y_1(t) \quad \wedge \quad P_{\text{grid}}^{\text{exp}}(t) \leq M y_2(t) \quad \wedge \quad y_1(t) + y_2(t) \leq 1.$$

where $M$ is a very large fixed value (i.e., $M = 10^{12}$). Since the third constraints eliminates the possibility of $y_1(t) = y_2(t) = 1$, each one of the two fundamental flow variables will have an upper bound of zero should the optimization decide to set a non-zero value for the other one.

On the other hand, the behavior of the battery is implemented by imposing a set of constraints on its state of charge $E_{\text{batt}}$ which also link its operation to the corresponding net discharge power flow $P_{\text{batt}}^{\text{net-disch}}$. The primary integral expression used to model the battery is given by

$$(\forall t \neq t_0) \quad E_{\text{batt}}(t) = \eta_{\text{batt}} E_{\text{batt}}(t - T_s) - P_{\text{batt}}^{\text{net-disch}}(t) T_s$$

whereby in each time step the storage value is increased or decreased based on the ammo ut if incoming or outgoing flow. Also, $\eta_{\text{batt}}$ denotes battery energy retention coefficient allowing for a small amount of spontaneous discharge, $t_0$ is the initial time step and $T_s$ the sample rate.

Finally, the load curve is envisioned to have a predefined amount of flexibility such that, in every consecutive horizon-long window of length $T$, the power value can be increased or decreased between predefined bounds while the total energy consumed must remain the same as suggested by the forecasted power profile $P_{\text{load}}^{\text{forecast}}$. The primary constraint ensuring this states that

$$\sum_{t \in (t_0, t_0+T)} P_{\text{load}}(t) = \sum_{t \in (t_0, t_0+T)} P_{\text{load}}^{\text{forecast}}(t).$$

In addition, the load variable is bounded by the upper and lower flexibility limits as given by

$$(\forall t) \quad P_{\text{load}}^{\min}(t) \leq P_{\text{load}}(t) \leq P_{\text{load}}^{\max}(t),$$

in the same manner as all other variables have bounds corresponding to their physical limits. One particular exception to this rule is that the battery state of charge at the final time step is limited such that it equals the same value that was present at the beginning of the simulation horizon.

In summary, once the present set of constraints is expanded to all mentioned variables and implemented, the resulting set of equations can be solved using mixed-integer linear programming techniques. Operational cost value is set as the objective of this optimization. In other words, the objective function is derived by multiplying the grid import curve with prices, with the revenue achieved from grid exports subtracted. In the particular case of the proposed cloud platform, this service is implemented as a Python script using the Python-MIP library (Túlio A.M. Toffolo and Haroldo G. Santos, 2024) coupled with the open source Coin-or branch and cut CBC (COIN-OR Foundation, 2024) solver mixed-integer linear programming problems. The service itself is packaged as a docker container and can be easily run on any Linux machine, similarly to the previously discussed services.

### 4.4. Consumer recommender

The consumer recommender service is executed as one of the final steps of the forecast-optimize-control loop of the platform. The service analyzes the optimal profile, delivered by the energy dispatch optimization service, for the next day for each pilot's building. The analysis of the optimal profile allows the selection of the most suitable predefined recommendation for the specified period and delivers it to the participant to encourage manual DR actions. This analysis also particularly considers energy prices in case the participant is associated with a time-of-use tariff which, by nature, contains at least one period with reduced energy costs. Its application aims to help in bringing the consumption curve closer to what is suggested by the optimization service.

The resulting notifications aim to suggest to the participants that they should perform manual control actions to align the energy consumption of the facility they manage to the optimal energy profile provided by the energy dispatch optimization service. Three types of recommendations have been implemented. The first focuses on changing the period of energy consumption to align with the hours of extra generation. The second aims to reduce energy consumption in the building. The third serves as a reminder to the participant of the period of free tariff, if applicable.

The Consumer recommender service is executed in a periodic and configurable cycle of time and sends the recommendations to the participants the day before, also considering the user preferences defined in the accompanying mobile app. The delivery of the recommendation is performed in the form of push notifications sent to the accompanying mobile application through the Google Firebase service. The notification is presented on the smartphone using the same mechanism that mobile application users already know and use, thus avoiding the introduction of an additional learning barrier. Notifications also provide the option to send feedback on the received recommendation, informing us whether they are willing to apply it. By gathering feedback from users, the aim is to qualitatively validate the recommendations provided, ensuring that manual control actions are being implemented and aligned with user preferences.

### 4.5. Thermal energy consumption optimization

In line with the objective of optimizing energy efficiency, the proposed platform integrated Mitsubishi Electric air-to-water (A2 W), and air-to-air (A2 A) heat pumps to modify the thermal energy consumption profiles of participating users. By enabling remote control of these systems, the platform dynamically optimized both domestic hot water (DHW) and space heating/cooling operations in accordance with the equipment capability, the optimal energy load profiles, and production forecast data. This integration allowed for scheduled control adjustments to maximize the local utilization of renewable energy while minimizing energy consumption during periods of low production, thus extending the functionality solely provided by the energy dispatch optimization approach by specifically targeting the thermal assets. In addition to enhancing energy efficiency, this service was designed to maintain optimal thermal comfort across a range of building types, from individual residential units to community-level facilities.

To validate the system's performance, critical prerequisites such as data integrity, system connectivity, and the initial state of the heat pump equipment were verified prior to implementation. The installed A2 W heat pumps integrated with DHW were subjected to a control loop designed to force the DHW tanks to heat during periods of predicted peak solar energy production. This implementation demonstrated the platform's capability to optimize energy usage in synchronization with renewable energy generation, while concurrently maintaining user thermal comfort. The operation included the following steps:

1. Heat pump operational status verification: Confirm that the heat pump system is active and functioning within the defined parameters.
2. Production prediction availability validation: Ensure that a valid energy production forecast is available for the specific household.
3. Maximum prediction value and optimal curve computation: Calculate the peak predicted energy production for the day to identify the optimal period for energy usage or, alternatively, consult the optimal profile curve generated by the energy dispatch optimization service to adjust the temperature set point based on the recommended periods of optimal energy usage.
4. Control signal transmission: Send the control signal to activate the DHW tank heating system during the identified optimal production window.

The temperature set point for the heat pump was scheduled to be adjusted every 15 min, aiming to shift energy demand without compromising the pre-established thermal comfort of building occupants. This approach enabled remote modifications to the heat pumps' operational set points, allowing the system to either increase or decrease energy consumption during specific intervals. To ensure user comfort, manual override functionality was enabled, allowing occupants to adjust the thermostat settings as needed.

The primary objective of this control strategy was to create a thermal buffer within the designated building zone, optimizing the heating and cooling systems. When the heat pump was operating in heating mode, and the optimal energy load profile indicated increased energy availability during a 15 min interval, the temperature set point was incremented by one degree Celsius. On the other hand, if the profile suggested minimizing energy usage, the set point was decreased by one degree Celsius. For cooling mode, if the optimal profile suggested increasing energy consumption, the temperature set point was reduced by one degree Celsius, and if it indicated lower energy consumption, the set point was increased by one degree Celsius. These dynamic adjustments were made in accordance with the baseline set points predefined by the user within the system.

As with the previous scenario, the availability of accurate and reliable data was critical to ensure the successful implementation of this use case. Missing or incomplete data, such as energy consumption figures, energy production forecasts, tariff structures, or energy demand predictions, could negatively impact the results. The steps involved in executing this use case are outlined as follows:

1. Historical data verification:
    - Heat pump operational status check - Confirm that the heat pump is operational and functioning as expected.
    - Heat pump operation mode - Identify the current operational mode, such as heating, drying, cooling, fan only, or automatic mode.
    - Temperature set point retrieval - Download the current temperature set points for each zone within the facility.
2. Apply analytical services:
    - Optimal consumption curve availability - Confirm that an optimal energy consumption profile is available for the specific facility.
3. Control signal activation:
    - Temperature set point adjustment - Adjust the temperature set point based on the optimal consumption profile and its associated characteristics.
    - Timestamp logging - Record the exact time at which the adjustment was applied.
    - Facility identification - Specify the facility to which the control adjustment is being applied.
    - Device specification - Identify the specific zone or area within the facility where the adjustment is taking place.
    - Action definition - Specify the type of control action to be executed on the heat pump system.

This use case enabled the temperature in each zone of the building to be adjusted individually, allowing the heat pump to operate efficiently by targeting specific zones for heating or cooling. This zone-based control strategy improved overall energy efficiency while ensuring that the system met the thermal comfort requirements for each defined area.

## 5. Results and discussion

Once the system was designed, developed, implemented, and enough time had passed for sufficient baseline and validation data to be collected, before and after the start of control loop application, the obtained results should be thoroughly analyzed. With the overall goal of determining system effectiveness, the use cases presented in the next sections demonstrate the actions performed in the project's pilot islands using the platform in both electrical and thermal domains. Each pilot site applied a specific strategy in different time periods, in line with the project's goals and requirements, depending on the installed equipment and observed time span, with different strategies and control logic.

As a result of these actions, in the electrical use case applied in the Spanish pilot, all three facilities present a reduction of mean grid power consumption with 41 W for LG-A, 55 W for LG-B and 189 W for LG-C, corresponding to a relative change of 32%, 15% and 50%, respectively over the period of use case application. For thermal applications, the daily percentage of electricity used for heating the DHW tank during peak period (17:00–20:00) in Ireland, showed a reduction from 7.26% to 0 in AI-A, and from 26.36% to 19.54% in AI-B. Additionally, modifying the temperature setpoint in space heating in the Italian pilot led to a reduction in energy consumption from 1280 Wh/day to 467 Wh/day across full days, and from 420 Wh to 300 Wh during peak hours. The full characteristics of the use cases are discussed in more detail in the sections that follow.

### 5.1. Electrical use case

The primary, however not the only, target of the cloud platform and control system depicted in this paper is the electric domain. Therefore, the first portion of the result analysis presented in this section focuses on the methodology utilized for collecting, processing, and presenting variations in the electric power consumption depending on the equipment setup and control system application.

#### 5.1.1. Scenario setup

In order to assess whether the implementation of the integrated cloud platform has had tangible effects on the energy balance of the

**Table 5**
Time frames for the reference period and two selected use case scenarios for each facility, with dates formatted as YYYY–MM–DD.

| Facility | Reference period | | Scenario #1 | | Scenario #2 | |
|---|---|---|---|---|---|---|
| | start | finish | start | finish | start | finish |
| LG-A | 2022–05–01 | 2022–08–01 | 2022–10–06 | 2022–11–21 | 2023–03–10 | 2023–05–01 |
| LG-B | 2022–06–01 | 2022–09–01 | 2022–09–21 | 2022–10–24 | 2023–03–09 | 2023–05–12 |
| LG-C | 2022–06–20 | 2022–08–01 | 2022–09–21 | 2022–10–24 | 2023–03–10 | 2023–05–10 |

targeted users, a collection of data from facilities in La Graciosa was extracted during the lifetime of the project so that it can facilitate a statistical and numerical analysis. As the equipment installation and initial setup phase consumed the majority of the first half of 2022, the energy management infrastructure on most of the pilot installations had been completed before May or July. The system was left to operate on its own, using default settings that are provided by the Victron equipment as the selected vendor for inverters. This process continued until the beginning of September when the control loop supported by the platform depicted in this paper was connected to the inverters and allowed to select the desired setpoint value for the power flow at the point of common coupling (grid connection) based on the output of the optimization which is, in turn, informed by forecaster outputs and limitations given in the semantic repository. What followed was a sequence of different scenarios during which different optimization and control setups were applied to the facilities. As presented in de Marcos et al. (2023), a major distinction should be made between three time spans:

- Reference period (applied between early May–June 2022 and September 2022) during which the equipment was running in its default settings without the intervention of the cloud platform.
- Scenario #1 (applied between early September 2022 and January 2023) during which different pricing profiles were applied with the primary goal of cost minimization.
- Scenario #2 (applied between March 2023 and June 2023) during which the price profiles were set up to incentivize self-sufficiency and particularly penalize (excessive) grid power imports.

The mentioned Scenario #1 application period can be further classified into temporal sections during which different tariff profiles are tested (fixed, time-of-use, based on wholesale market, etc.). With this variety in mind, only one time period corresponding to a single tariff selection will be selected as a showcase for the scenario analysis.

The exact date and time at which the equipment became operational, the scenario application started along with corresponding tariff profiles varies from facility to facility. This is mostly due to each facility being manually managed and only included once all the necessary preparations in terms of both hardware and software setups were resolved. Once the monitoring data was collected and parsed, a representative time span without discontinuities was selected from each category. These ranges are outlined in Table 5 and they represent the temporal criteria for the following grouping of data.

Table 5 also lists the three selected facilities, labeled LG-A, LG-B, and LG-C to preserve user anonymity, that are utilized for the following analyses and discussion. All of them are residential units and they were chosen amongst other project participants as they have exhibited the most stable overall connection to the platform to warrant a meaningful statistical comparison with sufficient data, along with displaying a responsive nature to the desired setpoints. With this selection in mind, Table 6 presents a selection of parameters extracted from the platform's semantic repository that are crucial in defining the corresponding model instance for optimization and forecasting. Other facilities, omitted from the following analyses, were either lacking the necessary hardware requirements to fully facilitate the described scenarios or the scenarios were applied in different ways.

With the goal of further illustrating the optimization and control process, a selection of key variables has been extracted for a particular

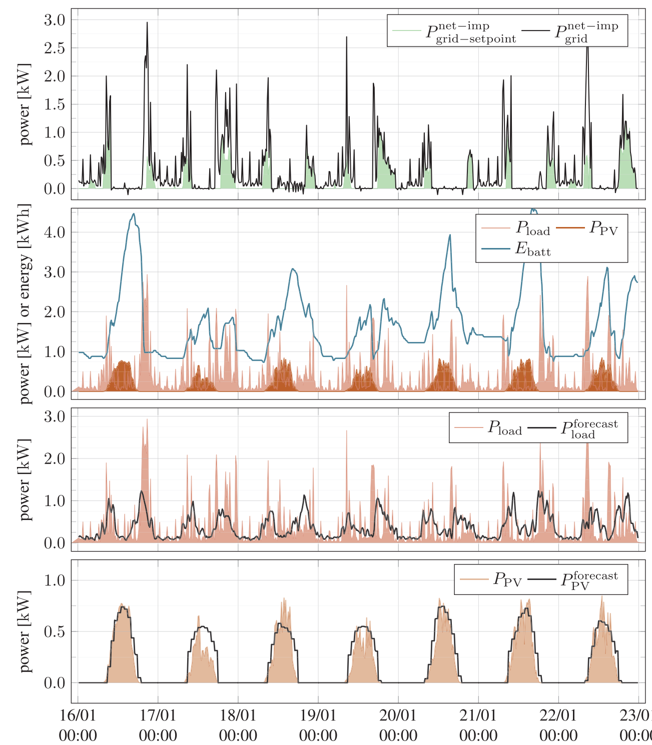


**Fig. 6.** Example of key variable trends during a use case period. From top to bottom: comparison of net grid import with its setpoint; power demand, PV production, and battery state of charge; actual versus forecasted power demand; and actual versus forecasted PV production.

facility, LG-A, and presented in the form of time series as given in Fig. 6. Here, the desired setpoint power flow value is depicted using a filled green area. The black line in the topmost figure is the measured net power import from the grid and, in the ideal scenario, it should strive to follow the path outlined by the setpoint. However, in the case there is a mismatch between the forecasted profiles and the actual measurements, or if the battery is unexpectedly saturated or depleted, deviations are possible and expected. On a lower level, the setpoint provided by the cloud platform is treated as a suggestion with the background logic ensuring that the energy balance is maintained, also resulting in potential deviations from the targeted power curve from time to time.

As also evident from the results shown in Fig. 6, deviations between the forecasted and measured values, displayed with the same sampling rate, are expected when analyzing the demand curve. While the demand forecasting service outputs an accurate estimate regarding the timings where maximum energy needs are located, as well as the overall energy consumption, predicting actual peak values is much more difficult due to the intrinsic stochastic nature of the underlying user behavior. On the other hand, the production forecasting relies on more accurate indicators such as solar irradiance that are closely correlated with the targeted PV output values. As a result, the PV forecast almost fully matches the actual measured RES production.

**Table 6**
Key parameters extracted from the ontology for the selected facilities, used to instantiate optimization models, including grid connection limits, battery storage characteristics, and PV system capacity.

| Facility | Grid connection [kW] | | Battery parameters [kWh] or [kW] | | | PV capacity [kW] |
|---|---|---|---|---|---|---|
| | $\max P_{\text{grid}}^{\text{imp}}$ | $\max P_{\text{grid}}^{\text{exp}}$ | $\max E_{\text{batt}}$ | $\max P_{\text{batt}}^{\text{charge}}$ | $\max P_{\text{batt}}^{\text{disch}}$ | $\max P_{\text{PV}}$ |
| LG-A | 3.30 | 2.40 | 4.90 | 2.00 | 3.00 | 1.95 |
| LG-B | 9.20 | 2.40 | 8.00 | 4.90 | 6.90 | 2.60 |
| LG-C | 3.45 | 2.40 | 4.00 | 2.60 | 3.60 | 1.95 |

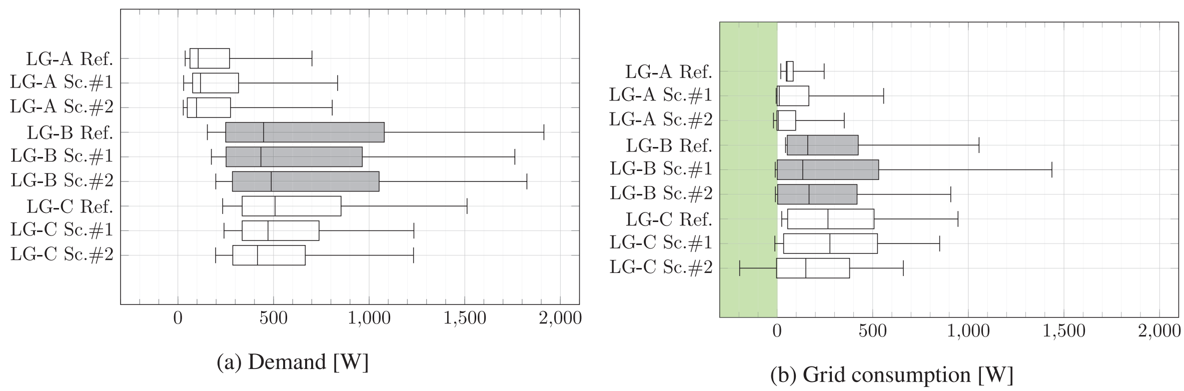


**Fig. 7.** Key statistical characteristics overview depicted using box plots of (a) power demand $P_{\text{demand}}$ and (b) grid power consumption $P_{\text{grid}}^{\text{net-imp}}$ variables during the three selected periods.

### 5.1.2. Data analysis

The numerical analysis of the selected data first entails a statistical characterization of the demand variable in all three periods. Fig. 7(a) presents a summary of values describing demand for the three facilities during the three periods in the form of a box plot. This plot utilizes a set of percentiles defined at different points to present a simplification of the distribution. For a random variable $X(t)$, its $N$th percentile can be defined as some value $a$ for which the probability of $X$ being less then or equal to $a$ is $N$ per cent, explicitly written as

$$p_N(X(t)) = a \quad \Longleftrightarrow \quad P(X(t) \leq a) = N/100.$$

While a typical box plot defines the outer whiskers at $p_{25} - 1.5 \cdot (p_{75} - p_{25})$ and $p_{75} + 1.5 \cdot (p_{75} - p_{25})$, or in other words $1.5 \cdot IQR$ away from 25th ($p_{25}$ or first quartile) and 75th ($p_{75}$ or third quartile) percentile, the presentation given in Figs. 7(a) and 7(b) sets them at the 10th and 90th percentile, respectively, to avoid depicting demand with nonexistent negative values and remove outliers. The inner box is then drawn in a typical manner between $p_{25}$ and $p_{75}$ with the median value corresponding to $p_{50}$ being denoted with a thin line. These key values, along with basic statistical attributes depicting mean and standard deviation metrics are also presented for each facility and each period in Tables 7–9.

With the goal of providing a baseline for the following analysis of control system application impacts on the grid power exchange variable, changes in demand characteristics must first be scrutinized. In this regard, LG-A exhibits a slight shift of demand towards higher values during Scenario #1 application as evidenced by differences in mean and median. However, the majority of the distribution can be found within the same range in all three periods. A similar conclusion can also be made for LG-B in which the distributions shift first towards lower values during Scenario #1, and then back towards higher values during Scenario #2. Finally, LG-C shows a clear reduction in demand first from the Reference period to Scenario #1, and subsequently from Scenario #1 to Scenario #2. In order to numerically summarize the changes in the demand characteristics between the Reference period and Scenario #2 in particular, as these values are of interest when assessing the control system effectiveness, Table 10 has been derived from the data already presented in Tables 7, 8 and Table 9.

Transferring from demand to grid consumption analysis, as illustrated in Fig. 7(b), it can be observed that all three facilities display a gradual shift towards the left i.e., towards the 'self-sufficient' zone. This area, highlighted in green, is defined as the half-plane of the graph

**Table 7**
Key statistical attributes of the demand measurements $P_{\text{load}}$ [W] for facility LG-A across the reference and scenario periods, including basic statistics and selected percentiles.

| Period | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 285 | 466 | 38 | 63 | 106 | 270 | 701 |
| Sc. #1 | 316 | 479 | 30 | 77 | 118 | 317 | 835 |
| Sc. #2 | 302 | 501 | 28 | 49 | 97 | 275 | 807 |

**Table 8**
Key statistical attributes of the demand measurements $P_{\text{load}}$ [W] for facility LG-B across the reference and scenario periods, including basic statistics and selected percentiles.

| Period | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 776 | 751 | 154 | 250 | 448 | 1079 | 1914 |
| Sc. #1 | 725 | 685 | 175 | 252 | 434 | 964 | 1762 |
| Sc. #2 | 785 | 723 | 198 | 285 | 488 | 1052 | 1825 |

**Table 9**
Key statistical attributes of the demand measurements $P_{\text{load}}$ [W] for facility LG-C across the reference and scenario periods, including basic statistics and selected percentiles.

| Period | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 709 | 584 | 234 | 336 | 508 | 853 | 1512 |
| Sc. #1 | 632 | 495 | 241 | 336 | 471 | 738 | 1234 |
| Sc. #2 | 587 | 504 | 197 | 287 | 416 | 666 | 1232 |

**Table 10**
Change in key statistical attributes of the demand measurement $P_{\text{load}}$ during the application of Scenario #2 relative to the Reference period, expressed in absolute terms [W] for all three facilities.

| Period | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| LG-A | 17 | 35 | −10 | −14 | −9 | 5 | 106 |
| LG-B | 9 | −28 | 44 | 35 | 40 | −27 | −89 |
| LG-C | −122 | −80 | −37 | −49 | −92 | −187 | −280 |

**Table 11**
Key statistical attributes of the grid power exchange measurements $P_{\text{grid}}^{\text{net-imp}}$ [W] for facility LG-A during the reference and scenario periods, including mean, standard deviation, and selected percentiles.

| Facility | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 128 | 341 | 19 | 48 | 52 | 84 | 246 |
| Sc. #1 | 175 | 400 | −5 | 0 | 11 | 166 | 557 |
| Sc. #2 | 87 | 407 | −19 | −1 | 6 | 97 | 351 |

**Table 12**
Key statistical attributes of the grid power exchange measurements $P_{\text{grid}}^{\text{net-imp}}$ [W] for facility LG-B during the reference and scenario periods, including mean, standard deviation, and selected percentiles.

| Facility | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 367 | 528 | 44 | 53 | 160 | 424 | 1056 |
| Sc. #1 | 406 | 756 | −10 | 1 | 134 | 531 | 1437 |
| Sc. #2 | 312 | 503 | −9 | 3 | 167 | 418 | 908 |

**Table 13**
Key statistical attributes of the grid power exchange measurements $P_{\text{grid}}^{\text{net-imp}}$ [W] for facility LG-C during the reference and scenario periods, including mean, standard deviation, and selected percentiles.

| Facility | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | mean | std | $p_{10}$ | $p_{25}$ | med | $p_{75}$ | $p_{90}$ |
| Ref. | 376 | 516 | 24 | 55 | 266 | 507 | 946 |
| Sc. #1 | 336 | 573 | −12 | 34 | 276 | 525 | 850 |
| Sc. #2 | 187 | 508 | −196 | −3 | 150 | 379 | 660 |

corresponding to negative grid consumption, or in other words, when a facility behaves as a net exporter. However, when looking at the given diagram, results from Scenario #1 should be observed only in the context of validating if the control system can have an impact on the shape of the grid consumption distribution, as the results correspond to tariff profiles different in nature. And, indeed, when looking at the key statistical characteristics during the application of Scenario #1, a clear distinction can be made from the Reference period.

On the other hand, Scenario #2 is expected to have a more clear and direct impact on grid consumption as the corresponding criterion is set such that grid imports are directly disincentivized. When observing the graphical representation of the key statistical characteristics of the net grid power consumption shown in Fig. 7(b) as well as the accompanying Tables 11–13, it can be deduced that the application of the control system does indeed have the desired impact on the power exchange. In addition to individual numerical results per facility, a summary of metric changes between the Reference period and Scenario #2 in terms of grid power characteristics is given in Table 14.

When these results are compared against the summary from Table 10, it can be deduced that the mean, lower percentiles as well as the median of grid consumption are shifted deeper into the 'self-sufficient' zone than the values from Table 10 would solely suggest. In cases where Table 10 would indicate an increase such as the mean demand for LG-A and LG-B and median for LG-B, the results from Table 14 actually either present noteworthy reductions in the former, or a minimal increase in the latter case, with this increase being, for example only 7 W as oppose to the corresponding demand increase of 40 W. The only cases where a comparative analysis of demand changes and grid power changes may hint to the limitations of the control system are in the upper percentiles, particularly for LG-A. However, even when these values for the grid power are scrutinized, they can be found to be, in the worst case scenario, approximately equal to the corresponding demand changes.

The discussed improvement could also, at least in theory, be attributed to an increase of PV production between the two periods thus resulting in a reduction in overall grid power consumption. However, as defined previously, the Reference period was applied in late summer while Scenario #2 was applied during spring. Since La Graciosa, the island where the three facilities are located, is in the northern hemisphere at an approximate longitude of $30^\circ N$, the PV arrays should not display a larger energy potential during Scenario #2 application as a result of differing meteorological conditions. On the other hand, the application of the system during Scenario #2 may have had a positive impact on the utilization of the battery, in turn freeing up additional potential flexibility for storing excess PV production that is not consumed at the instant it is produced. A deeper analysis of this phenomenon may be of potential interest but warrants a more detailed investigation that is beyond the scope of this paper.

In conclusion, the direct control in terms of setpoint definition provided by the platform is found to have a noteworthy effect on the grid power consumption, as reflected in the analysis of a predetermined set of key statistical characteristics. This effect, as presented in the results, can differ depending on the set tariff profile. The shift towards 'self-sustainable' operation is particularly notable when analyzing the behavior of the selected facilities during the application of Scenario #2, showcasing that potential improvements can be made upon default settings that the inverter utilizes and reinforcing potential benefits that smart control can bring to island communities and positive energy neighborhoods in general. However, this direct control was not the only utilized means of energy management, as will be expanded upon in the following paragraphs.

#### 5.1.3. End user feedback loop

Engaging participants in the management of energy usage is a key factor in the successful application of innovative energy management systems. The mobile application, developed in conjunction with the web-based control platform, allows participants to monitor the equipment installed in the building, providing real-time information on the renewable energy generated by photovoltaic panels, the energy stored in the battery, as well as forecast data indicating the expected energy production and consumption for the current day. The app also provides a set of graphical tools to visualize historical data gathered from the installation, enabling the participants to track how much energy has been produced and consumed. Users can filter data by day, week, month, and year. Additionally, the app can receive text-based recommendations from the platform and store them, allowing participants to review previous recommendations.

Through the utilization of the notification delivery capabilities, a series of DR actions, referred to as "End-user appliance control" were implemented across all three pilot islands. In La Graciosa, these actions were applied between January 1st, 2023, and March 7th, 2023, in San Pietro from April 20th, 2023, to May 21st, 2023, and finally in Aran from May 25th, 2023, to June 27th, 2023. In each pilot, participants were selected to receive these notifications based on a set of specified criteria. On the hardware side, participants were required to have a combination of RES and storage systems installed in their facility in order to be capable of providing the necessary energy flexibility. On the software side, the corresponding facilities needed to have energy demand and PV production forecasts available, with the optimization service providing the optimal power setpoint.

Table 15 provides an overview of the recommendations delivered and the participants involved in this specific use case. As the feedback functionality was optional, users were not required to confirm whether they had followed the recommendations. Even though the table clearly illustrates users' reluctance to provide feedback, when the total number of delivered recommendations is taken into account, a positive correlation has been observed between energy consumption and the periods during which an increase in demand was suggested. This indicates that users were likely responding to the messages even without explicitly reporting their actions. As can be observed in Fig. 6, the demand curve displays alignment in several cases with PV production. This suggests

**Table 14**
Change in key statistical attributes of grid power exchange $P_{\text{grid}}^{\text{net-imp}}$ during the application of Scenario #2 relative to the Reference period, expressed in absolute terms [W] along with a relative bar representation truncated at ±100%.

| | Basic stats | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| Facility | $\Delta$mean | $\Delta$ std | $\Delta p_{10}$ | $\Delta p_{25}$ | $\Delta$med | $\Delta p_{75}$ | $\Delta p_{90}$ |
| LG-A | -41 | 66 | -38 | -49 | -46 | 13 | 105 |
| LG-B | -55 | -25 | -53 | -50 | 7 | -6 | -148 |
| LG-C | -189 | -8 | -219 | -58 | -117 | -128 | -286 |

**Table 15**
Summary of user engagement and manual control activities across three pilot sites, including number of facilities, mobile app installations, actively notified facilities, duration of participation, total recommendations sent, and user feedback received.

| Number of | La Graciosa | San Pietro | Aran |
|---|---|---|---|
| Facilities in total | 22 | 29 | 21 |
| Mobile app installs | 15 | 20 | 10 |
| Facilities actively notified | 4–7 | 8 | 5 |
| Total days | 66 | 32 | 32 |
| Recommendations | 312 | 232 | 133 |
| Feedback received | 3 | 3 | 3 |

that incorporating direct user interaction of this nature can provide added value in a platform such as the one proposed in this paper. Despite the absence of a fully closed feedback loop, this approach proved effective in influencing user behavior and generating energy savings.

### 5.2. Thermal use case

Building upon the previously demonstrated optimization loop, and with the goal of expanding control to assets beyond just electrical systems, heat pumps were employed to modify the usual thermal energy usage behavior of participants in the facilities. The primary objective was to utilize the platform and its components integrated with the thermal system. Energy production forecasts and optimal energy profile curves for the buildings guided decisions on when to increase energy consumption or reduce usage during specific periods.

Two use cases were tested to explore the thermal control capabilities of the heat pumps integrated with the platform. In the first use case, conducted on the Aran Islands with A2 W heat pumps, the focus was on optimizing the DHW heating schedule by aligning the heat pump's operation with predicted peak hours of local photovoltaic energy production. The second use case, applied at both the Aran Islands and San Pietro pilots, involved adjusting the thermostat temperature set point in 15 min intervals to shift energy usage in line with the optimized energy use profile, but without compromising thermal comfort. This use case included A2 A heat pumps at the San Pietro site. In the Irish pilot, control actions were performed on five heat pumps located in two community buildings and three residential buildings, with results presented here focusing on participants refereed to as AI-A and AI-B, named in this way to preserve their anonymity. In the Italian pilot, two heat pumps were controlled, one in a residential building and one in a community building, refereed to here as SP-A and SP-B. These use cases demonstrated how control actions, such as rescheduling DHW heating hours and adjusting thermostat set points, could balance energy efficiency with user comfort.

#### 5.2.1. Optimizing DHW heating schedule

The first use case, implemented in the Aran Islands pilot, focused on optimizing the DHW heating schedule. A command was sent to the heat pumps to heat the water in the hot water tank once per day in the predicted peak production hour, aligning the heat pump's power usage with the optimal production period. This approach focused on maximizing the on-site utilization of locally produced renewable photovoltaic energy. By prioritizing local energy consumption over

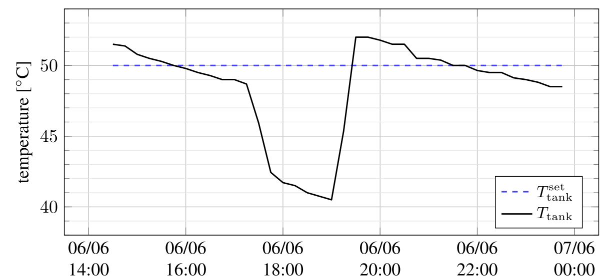


**Fig. 8.** Hot water tank temperature measurements $T_{\text{tank}}$ and setpoint values $T_{\text{tank}}^{\text{set}}$ for AI-B on June 6th, 2023, under conditions without HP intervention.

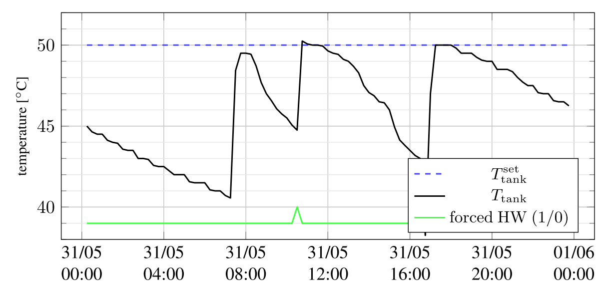


**Fig. 9.** Hot water tank temperature measurements $T_{\text{tank}}$ and setpoint values $T_{\text{tank}}^{\text{set}}$, and forced hot water (HW) activation status (1 = on, 0 = off) for AI-B on May 31st, 2023, under conditions with HP intervention.

exporting it to the grid, the approach aimed to decrease the need for external energy supply during periods of high demand.

In this process, the platform verifies the relevant data and then identifies and sets a schedule for energy usage. The variables controlled during the application of this use case included forcing the activation of the DHW tank heating and setting the maximum allowable temperature for the DHW tank, which would deactivate the heating upon reaching the predefined threshold. This use case was tested from May 25th, 2023, to June 26th, 2023. Initial daily tests were conducted from May 25th to June 1st, 2023, with intermittent testing on June 6th, 14th to 17th, 19th, 21st, 22nd, and 26th, 2023.

The target temperature could be adjusted according to user habits and preferences, with a minimum recommended temperature of 20 °C and a maximum of 60 °C. Specific settings for each user were noted and incorporated into the system on a per-household basis. As illustrated in Fig. 8, from June 6th, the heat pump installed in facility AI-B typically heats the water automatically when the tank temperature reaches 40 °C.

Fig. 9 illustrates an action to force the tank to heat the water when the prediction for PV production reached its maximum values. This action promotes self-consumption of the energy generated by the PV system, also avoiding turning the system on during the peak usage hours of the grid in Ireland. Fig. 9 shows the temperature increase, based on the action guided by the peak prediction PV production times, leading to increased energy self-consumption and reduced reliance on the grid during peak hours (17:00–20:00). This action led to a decrease in the average usage of the grid to heat the water tank during peak hours, from 16.83% to 11.91%, considering all days when the use case

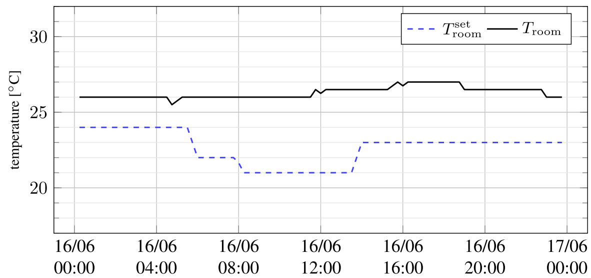


**Fig. 10.** Example of room temperature measurements $T_{\mathrm{room}}$, and corresponding setpoint values $T_{\mathrm{room}}^{\mathrm{set}}$ for SP-A on June 16th, 2023, under conditions without HP intervention.

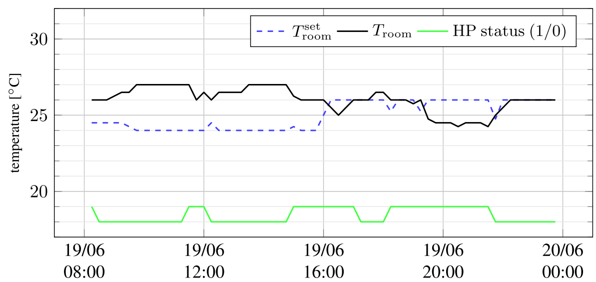


**Fig. 11.** Example of room temperature measurements $T_{\mathrm{room}}$, setpoint values $T_{\mathrm{room}}^{\mathrm{set}}$, and HP status (1 = on, 0 = off) for SP-A on June 19th, 2023, under conditions with HP intervention.

was applied. In AI-A, the usage reduced from 7.26% to 0%, and in AI-B, from 26.36% to 19.54%.

### 5.2.2. Optimizing temperature set points

The use case was tested over several dates in June 2023, specifically on the 14th, 15th, 16th, and from 18th to 24th, in the San Pietro pilot. Based on the collected temperature data for each building, a modified hourly temperature set point curve was created by the thermal energy consumption optimization service of the proposed platform for each zone of the building. This curve was delivered daily to support the new proposed energy usage pattern. To maintain comfort, the temperature was adjusted based on the last recorded set point temperature of the area. This approach involved adjusting the heat pump's temperature set point to create a buffer of heat or cold, depending on the recommended action from the optimal curve and the heat pump operation mode. In this scenario, when the curve indicated that the system should consume more energy, the temperature was increased; if it indicated avoiding usage, the temperature was decreased.

In the example of this use case depicted in Fig. 10, the initial setpoint temperature of the building was 23 °C before applying any controls. The optimized actions from the platform started at midnight, with the control strategy to avoid energy usage by increasing the setpoint temperature by 1 °C, resulting in the setpoint of 24 °C from 00:00 to 06:00. At 06:00, the setpoint was reduced to 22 °C to create a buffer of cold during the period when the user was suggested to use more energy. The user's schedule included an automated adjustment at 08:00 to align with their routine, changing the temperature again until the final action at 14:00 restored the initial setpoint of 23 °C. During this test, the heat pump remained off, meaning only the setpoint temperature was adjusted without affecting the actual room temperature. This test ensured that this approach allowed the users to maintain ultimate control over their heat pump system, both to maintain their temperature comfort levels if not in accordance with the optimized profile at that time and also ensuring energy conservation when facilities are vacant, or when the user does not want to turn on the system for other personal reasons. This approach was tested to guarantee that the system was ready when the user decided to turn on the heat pump.

In the scenario depicted in Fig. 11, the initial setpoint temperature of the building was 24.5 °C. The optimized actions started at 09:45, with the goal of avoiding energy usage by decreasing the setpoint temperature to 24 °C. With some minor manual adjustments in the meantime, at 16:00, the system adjusted the setpoint again to 26 °C to avoid using energy during this period. As opposed to the previously discussed case, in this scenario, the user turned the HP system on and off throughout the day, mostly following the temperatures suggested by the system. The results of these actions showed an overall reduction in the average energy consumption of the HP from 1280 Wh/day to 467 Wh/day across entire days, and from 420 Wh to 300 Wh during peak hours throughout the use case implementation.

## 6. Conclusion and future work

In summary, this paper presents the structure of an integrated cloud-based IT platform designed to provide energy asset management capabilities for RES-powered energy communities. The backbone of the platform is built upon three database technologies: relational, time-series, and semantic, augmented with a set of field-level interfaces for data acquisition and control, as well as a set of services based on machine learning, heuristics, and optimization, that provide forecasts of local expected energy production and consumption on a per-facility level, as well as an optimal energy dispatch strategy.

The primary goal of the platform was to provide a system with the capability of making use of the available computing power and give additional insight to the central optimization model. Namely, based primarily on previously collected data stored in the platform, forecasts should provide additional guidance in the optimization process, which can result in a variety of control action suggestions such as how to operate energy storage systems, when to activate particular assets like heat pumps, and what setpoints to set for EV charging or in the $H_2$ electrolysis process, etc. In doing so, the platform provides added value on top of what the algorithms that are given by default with the equipment already provide, facilitating an intelligent way to manage energy based on future predictions.

In the context of the REACT project, the platform was applied to a set of communities on geographical islands where, in different circumstances, different features could be tested. Specifically, facilities on the island of La Graciosa demonstrated the ability to reduce the mean electric grid power consumption by 41 W, 55 W and 189 W when the results from the period with the proposed platform in operation where compared to those obtained by running the algorithms that manage the energy flow through the inverter provided by its vendor. Furthermore, a custom user recommendation service was built on top of the proposed optimization solution, along with a system that schedules heat pump activations in line with the desired demand profile, as demonstrated in facilities on the Aran Islands showing reductions in DHW energy usage down to 0 during peak hours in one of the scenarios and in San Pietro, where the average energy consumption was reduced from 1280 Wh/day to 467 Wh/day.

The research topics central to the platform presented in this paper could benefit from additional testing with other assets supported by the platform, which, for various reasons, could not be included in the presented study. Often, local legislation is not aligned with the technical capabilities of the assets that contemporary energy communities are equipped with, thus limiting the theoretical possibilities of novel control strategies. Further exploration, once the policy is updated, could be beneficial for expanding the depicted results. In addition, particular importance should be placed on maintaining connection stability and continuous equipment uptime, particularly in remote use cases, as these have been noteworthy barriers to full platform utilization.

The scalability of the proposed solution is also another interesting point to consider in terms of potential future applications. From the very start, the research project that has produced the proposed cloud platform has maintained the concept of so-called follower islands. These are communities that are intended to serve as case studies for further project expansion in the future, in both technical and societal aspects. The findings provided in Salces et al. (2025) speak to the relationship between islanders' knowledge and attitude towards innovative energy solutions and their active participation in energy transitory projects. Improving awareness and knowledge through providing timely information, organizing training sessions and in person discussion are singled out as key drivers that would facilitate a fruitful relationship between residents and both the hardware and software they should interact with. As for the technical aspects, efforts are already underway at the time of writing to improve the implementation of the optimization, allowing it to automatically create energy infrastructure models based on the content of the ontology even with diverse energy assets utilized. This will allow the proposed platform to be applicable to more complex energy systems spanning multiple locations if needed, while maintaining all the flexibility described in the model definition stage. By maintaining the integration flexibility, legacy systems with existing assets and grid connections could be included in the optimization process requiring only minor modifications for monitoring and control.

Another barrier worth investigating are the potential policy barriers that may sometimes hinder the use of energy flexibility that platforms such as the one being proposed in this paper aim to exploit. For some time, it appears that research efforts in related fields have been ahead of applicable regulatory frameworks. While this issue was resolved in due time, even during the development of the proposed platform, the legality of self-consumptions and overproduction exporting was not fully resolved in some cases. On the other hand, inter and intra-community energy trading with locally sourced energy are key aspects of future energy markets and their proliferation should serve to make novel business models more feasible. This added flexibility will, by extension, increase the need for optimization and control of energy through newly introduced paths, further reinforcing the importance of platforms such as the one proposed in this manuscript. It should also be noted that differing regulation across boundaries may result in additional customization requirements that should be reflected in the model's constraints.

Although this work does not focus explicitly on ethical issues, ethical considerations were integrated throughout the platform's design and deployment phases. When handling user data in the forecasting, optimization, and recommender services, principles of data minimization, transparency, and user consent were taken into account. The platform was developed using secure communication protocols and data storage practices to safeguard sensitive energy and behavioral data. Additionally, the mobile app allowed users to provide feedback, reinforcing voluntary engagement. Ensuring fairness, privacy and inclusivity was essential during the development of this platform, particularly when considering its scalability across different contexts and different communities.

Nevertheless, despite all the encountered challenges, the obtained results clearly show a large potential for similar systems as a means to provide more efficient energy management and renewable generation utilization, key prerequisites for a sustainable future. In line with global energy trends and policy goals, such as the EU's climate targets, this platform's achievements support the transition towards lower emissions and optimized energy use, demonstrating its significance for sustainable development initiatives.

## CRediT authorship contribution statement

**Marko Jelić:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dayanne Peretti Corrêa:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dea Jelić:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lazar Berbakov:** Writing – original draft, Software, Methodology, Conceptualization. **Daniel Werner:** Writing – original draft, Software, Methodology, Conceptualization. **Md Nasimul Islam Maruf:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Ignacio Lázaro:** Writing – original draft, Software, Methodology, Conceptualization. **Izaskun Fernández:** Writing – original draft, Software, Methodology, Conceptualization. **Marcus Keane:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Nikola Tomašević:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

The data that has been used is confidential.

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