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Electric Vehicles Management for carbon neutrality in Europe

Deliverable D2.5
Integration of V2X in Energy Communities Management

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Executive Summary

The deliverable D2.5 – "Integration of V2X in Energy Communities Management" aims to propose various methodologies for the optimal management of energy communities, considering user's needs. The proposed methodologies include deterministic, stochastic, and metaheuristic optimization. These approaches are tailored for an energy community comprising battery energy storage systems (BESS), photovoltaic systems (PV), electric vehicles (EVs), electric vehicles supply equipment (EVSEs), generators, main grid import/export power, loads, and offers of up and down power reserves. Additionally, the vehicle-to-everything (V2X) capabilities of EVs and EVSEs are incorporated into the optimization strategies.

The methodology for the integration of V2X in energy communities' management includes *i)* technical specifications related to loads, PV systems, generators, BESSs, EVs, and EVSEs. Key data points include power consumption, contracted power, peak PV power production, and charging/discharging capacities for BESSs and EVs. Additionally, it involves processing user behaviour data, such as arrival and departure times, energy requirements, initial state of charge (SoC), willingness to utilize V2X technology, as well as data related to energy prices; *ii)* energy community management considering a deterministic optimisation considering day-ahead scheduling and real-time control; *iii)* energy community management considering metaheuristic model in which the Dandelion Optimizer algorithm is analysed; *iv)* Energy community management is addressed through a stochastic optimization framework that incorporates up and down power reserve services from both grid imports and BESSs.

By analyzing the obtained results, the performance of the proposed models can be validated. A use case (UC) representing an energy community with 20 consumers/providers was included. Notably, only the stochastic model incorporates up and down reserve power offers across 25 scenarios (combined 5 for load consumption and 5 for power generation). When compared to the metaheuristic and stochastic models, the deterministic model yields the best results due to the minimal uncertainty it addresses. It demonstrates optimal management of BESSs and EVs for charging and discharging. On the other hand, the metaheuristic model shows the poorest performance, consistently resulting in load reduction and curtailment. It also displays inefficiencies in the management of BESS and EV charging/discharging operations. The stochastic model, like the deterministic model, delivers optimal results in managing BESS and EV power. It prioritizes charging during periods of higher generator availability. However, due to the uncertainties it addresses, the stochastic model reduces BESS consumption. Nevertheless, it maintains the energy demand for EVs at the same level, ensuring that the comfort of e-mobility users is preserved.

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Acronyms

BESS	Battery energy storage systems
CS	Charging station
DE	Differential evolution
DER	Distributed energy resources
DO	Dandelion optimizer
EC-VPP	Energy community-based virtual power plant
EMS	Energy management system
ENS	Energy not supplied
EV	Electric vehicle
EVSE	Electric vehicles supply equipment
GA	Genetic algorithm
GHI	Global horizontal irradiance
HyDE-DF	Hybrid adaptive differential evolution with decay function
MBECs	Market-based energy communities
MGO	Mountain gazelle optimizer
OF	Objective function
PSO	Particle swarm optimization
PV	Photovoltaic
PyECOM	Python energy communities
RES	Renewable energy source
SoC	State of charge
UC	Use case
V2G	Vehicle-to-grid
V2H	Vehicle-to-home
V2X	Vehicle to everything

Nomenclature

B	Set of batteries
EV	Set of electric vehicles
G	Set of generators
L	Set of loads
W	Set of scenarios
$C_{t,b}^{B+}$	Energy price associated with the power charged by the batteries
$C_{t,b}^{B-}$	Energy price associated with the power discharged by the batteries
$C_{t,ev}^{EV+}$	Energy price associated with the power charged by the electric vehicles
$C_{t,ev}^{EV-}$	Energy price associated with the power discharged by the electric vehicles
$C_{t,g}^{G+}$	Energy price associate with the imported power by generators
$C_{t,g}^{G-}$	Energy price associate with the exported power by generators
$C_{t,l}^{c}$	Energy price associated with the loads that can be curtailed
$C_{t,l}^{ENS}$	Energy price associated with the energy not supplied for the system's loads
$C_{t,l}^{r}$	Energy price associated with the loads that can be reduced
$C_{Gen(g,t)}^{UP}$	Cost associated with up energy reserve
$C_{Gen(g,t)}^{Down}$	Cost associated with down energy reserve
$C_{Imp(t)}^{UP}$	Cost associated with adjustments in up power import reserves
$C_{Imp(t)}^{Down}$	Cost associated with adjustments in down power import reserves
$C_{Gen(g,t)}^{Op}$	Cost associated with actual generation output
$C_{t,b,w}^{B+}$	Cost associated with charging power for storage units
$C_{t,b,w}^{B-}$	Cost associated with discharging power for storage units
$C_{St(t,b,w)}^{minRlx}$	Cost associated with relaxation variable of power for storage units
$C_{t,ev,w}^{EV+}$	Energy price associated with the power charged by the electric vehicles
$C_{t,ev,w}^{EV-}$	Energy price associated with the power discharged by the electric vehicles
$C_{EV(t,ev,w)}^{minRlx}$	Cost associated with relaxation variable of power of electric vehicles
$C_{EV(t,ev,w)}^{reqRlx}$	Cost associated with relaxation variable of power of electric vehicles
$C_{t,l,w}^{c}$	Energy price associated with the loads that can be curtailed
$C_{t,l,w}^{ENS}$	Energy price associated with the energy not supplied for the system's loads
$C_{t,l,w}^{r}$	Energy price associated with the loads that can be reduced
F^{DA}	Cost associated with day-ahead operation
F^{RT}	Cost associated with real-time operation
$L_{t,l}^{c}$	Power load that can be curtailed
$L_{t,l}^{ENS}$	Power not supplied for the system's loads
$L_{t,l}^{r}$	Power load that can be reduced
$L_{t,l,w}^{c}$	Power load that can be curtailed
$L_{t,l,w}^{ENS}$	Power not supplied for the system's loads
$L_{t,l,w}^{r}$	Power load that can be reduced
$P_{t,b}^{B+}$	Power charged by the batteries
$P_{t,b}^{B-}$	Power discharged by the batteries
$P_{t,b,w}^{B+}$	Power charged by the batteries by scenario
$P_{t,b,w}^{B-}$	Power discharged by the batteries by scenario
P_{t}^{Imp}	Power import from the grid
P_{t}^{Exp}	Power export to the gird
$P_{t,ev}^{EV+}$	Power charged by the electric vehicles
$P_{t,ev}^{EV-}$	Power discharged by the electric vehicles

$P^{EV+}_{t,ev,w}$	Power charged by the electric vehicles
$P^{EV-}_{t,ev,w}$	Power discharged by the electric vehicles
$P^{G+}_{t,g}$	Power imported by generators
$P^{G-}_{t,g}$	Power exported by generators
$P^{minRlx}_{St(t,b,w)}$	Relaxation variable of power for storage units
$P^{minRlx}_{EV(t,ev,w)}$	Relaxation variable of power of electric vehicles
$P^{reqRlx}_{EV(t,ev,w)}$	Relaxation variable of power of electric vehicles
$P^{Op}_{Gen(g,t)}$	Actual generation output
$R^{UP}_{Gen(g,t)}$	Up power reserve requirement for generation units
$R^{Down}_{Gen(g,t)}$	Down energy reserve requirement for generation units
$R^{UP}_{Imp(t,w)}$	Adjustments in up power import reserves across each scenario
$R^{Down}_{Imp(t,w\ )}$	Adjustments in down power import reserves across each scenario
t	Time step index
$\pi_{(w)}$	Scenario's probabilities

1 Introduction

Energy communities are groups of individuals, households, or organizations that collectively manage and optimize their energy use, generation, and storage. They can include renewable energy sources (RES) such as PV system, BESS, and the integration of various types of consumers and prosumers such as EVs [1]. Hence, energy community management involves the coordinated organization and control of energy resources and consumption within a localized group or community. This concept is part of the broader transition towards a decentralized and sustainable energy system [2]. The main goal of energy community management includes enhancing energy efficiency, increasing the use of renewable energy, reducing energy bills, and improving energy security and resilience. These communities also aim to empower local stakeholders and promote energy democracy by giving users more control over their energy sources and consumption [2].

1.1 Scope and objectives

The primary objective of this document is to evaluate the effectiveness of various optimization models, including deterministic, stochastic, metaheuristic, in the management of energy communities. To achieve this, the models utilize data inputs from an energy community comprising the main grid, PV systems, BESSs, EVs, EVSEs, and typical load profiles. Moreover, notable simulation results demonstrated the suitability of both deterministic and stochastic models for energy community management. These models enhance the utilization of energy resources within the system and effectively manage the power of BESS and EV, ultimately contributing to the comfort and efficiency of the community.

1.2 Structure

The present document is divided into 4 sections. After the introduction section (Section 1), Section 2 provides insight into EV management in energy communities. Section 3 details the main simulation results. Finally, Section 4 wraps ups with some overall conclusions and recommendations.

1.3 Relationship with other deliverables

The EVs and charging station (CSs) power limitation used, as input data, in the proposed energy community management was adapted from the *D2.1 of the EV4EU project: Control Strategies for V2X Integration in Houses* [3]. The company demand data was adapted from the one used in the *D2.2 of the EV4EU project*: *Control Strategies for V2X Integration in Buildings* [4].

2 Electric Vehicle Management in Energy Communities

EV management in energy communities has garnered rapidly popularity [5], since EVs can work, for instance, as energy storage units within energy communities: their batteries can store excess renewable energy generated during peak times and discharge it back into the grid during periods of high demand [6]. Another application of EV management within energy communities is the potential to implement demand response strategies by leveraging EVs. By adjusting their charging patterns in response to real-time grid conditions, EVs can help stabilize the balance between energy demand and supply [7]. Moreover, in an energy community, vehicle-to-Grid (V2G) technology can be used to balance local energy flows, enhance grid stability, and support the integration of RES, additionally, V2G can create revenue streams by selling energy back to the grid [8]. EV smart charging can also provide significant benefits to energy community management by controlling the timing and rate of EV charging based on factors like energy prices, grid conditions, and user preferences [9]. Furthermore, by using locally generated renewable energy for EV charging, energy communities can reduce energy costs for participants. The integration of EVs with RES can significantly reduce carbon emissions. Energy communities promote sustainable energy practices, which contribute to lower overall environmental footprints [6].

2.1 Main challenges of Energy Communities

Energy communities offer a promising model for decentralizing energy systems and promoting RES adoption. However, they face several significant challenges that need to be addressed to ensure their successful implementation and sustainability. These challenges span technical, economic, regulatory, and social dimensions [10]. From a technical standpoint, integrating distributed energy resources (DERs) such as PVs, wind turbines, and BESS can lead to grid instability, particularly if not properly managed. Challenges like voltage fluctuations, frequency regulation, and reverse power flows may arise, necessitating the use of advanced grid management technologies [11]. Moreover, energy communities often involve a variety of technologies, including different types of RESs, smart meters, and energy management software, hence, ensuring that these systems can communicate, and work together effectively is a significant challenge [11].

Regulatory and policy barriers can also pose significant challenges for energy communities, as the regulatory frameworks in many regions remain underdeveloped or non-existent. This creates uncertainty for community members and potential investors. For example, legal definitions of energy communities, along with their rights and responsibilities, are often ambiguous, which can impede their formation and operation [11], [12]. Furthermore, energy communities frequently encounter challenges related to grid access, including high connection fees and complex procedures. Furthermore, existing tariff structures often undermine the economic viability of these communities, as they typically fail to recognize the benefits of local energy generation and consumption [11]. Social and behavioural factors can also pose significant challenges for energy communities. The success of these communities largely depends on the active involvement and engagement of their members. However, encouraging such participation can be difficult, especially in areas with low social cohesion or where residents lack interest or knowledge about energy issues [13]. Energy communities often involve collective decision-making, which can be complicated by differing interests and priorities among members. Ensuring transparent, inclusive, and effective decision-making processes is essential but challenging [13].

2.1.1 Energy Community Based Virtual Power Plants

Energy Community-Based Virtual Power Plants (EC-VPPs) represent an innovative paradigm that seamlessly integrates RESs, storage system like EVs and BESSs, and flexible energy consumption within a community. These EC-VPPs function as unified power plants, optimizing energy generation, storage, and consumption on a community-wide scale [14]. Moreover, essential components such as DER, an energy management system (EMS) for coordinating these resources and predicting energy demand, and smart grid infrastructure have positioned EC-VPPs as a prominent and sophisticated trend in the pursuit of decarbonization [14]. Hence, EC-VPPs can aggregate the energy generation, storage, and consumption capacities of multiple distributed energy resources within the community [14]. The EMS optimizes generation and consumption by leveraging real-time data, weather forecasts, and market signals [15]. This optimization may include load shifting, peak shaving, and demand response strategies, enabling the EC-VPP to participate in energy markets by selling excess energy or providing ancillary services, such as frequency regulation, to the main grid [7]. The benefits of Energy EC-VPPs encompass enhanced energy efficiency through the optimized use of local RESs and the reduction of energy losses typically associated with long-distance electricity transmission. These systems also contribute to increased energy independence for the community by diminishing reliance on centralized, fossil fuel-based power plants. Additionally, EC-VPPs present opportunities for revenue generation through participation in energy markets, reduce energy costs for community members, create local employment opportunities, and lower greenhouse gas emissions through the utilization of RES and the broader adoption of clean energy technologies [1].

2.1.2 Market Based Energy Communities

Market-Based Energy Communities (MBECs) are energy communities that operate within a market framework, where members can trade energy among themselves or with external markets. These communities utilize decentralized DERs and market-based mechanisms to manage energy generation, consumption, and trading [16]. MBECs are designed to empower local stakeholders, including households, businesses, and institutions, to generate, trade, and consume energy within a localized market framework. This approach seeks to enhance energy efficiency, promote the adoption of renewable energy, and foster economic benefits at the community level [16]. Therefore, members of a MBEC can buy and sell energy within the community or to the external grid, with transactions based on real-time pricing, contracts, or other market mechanisms. Energy prices within the community are typically determined by supply and demand dynamics, influenced by factors such as generation capacity, storage availability, and consumption patterns. Additionally, MBECs may interact with the broader grid, either by selling excess energy or purchasing additional energy when local generation is insufficient. These interactions are often governed by market participation agreements [17].

2.2 Integration of EVs in Energy Communities

The integration of EVs into energy communities is an increasingly significant area of research, as it aligns with broader goals of sustainability, energy efficiency, and the decentralization of energy systems. Incorporating EVs into these communities presents both opportunities and challenges, given that they function as both energy consumers and mobile energy storage units [18]. EVs can play different roles into the energy community, such as mobile energy storage units, providing flexibility to the grid by storing excess renewable energy and discharging it when needed by implementing, for instance demand response techniques [7]. EVs can engage in demand response programs, where their charging schedules are adjusted according to the needs of the electrical grid. This participation contributes to balancing supply and demand within the community [7]. In advanced energy communities, EVs can be integrated into local energy trading systems. In these systems, energy generated by residents, such as from solar panels, can be sold or shared with neighbours or the wider community [18]. Facilitating and encouraging the integration of EVs into energy communities requires the establishment of an adequate charging infrastructure. Developing a network of charging stations within these communities will enable EVs to recharge using locally generated renewable energy [18]. An EMS can enhance the integration of EVs within the community's broader energy management framework. The EMS optimizes the timing and location of EV charging based on factors such as energy availability, demand, and pricing [19].

2.3 Python Energy Communities (PyECOM) simulation platform

Python Energy Communities (PyECOM) is a Python-based tool crafted to support the analysis, simulation, and optimization of energy communities, that bring together diverse participants such as households, businesses, and public entities to collaboratively manage and share energy resources. PyECOM aims to enhance energy independence, reduce costs, and promote the adoption of RESs sources through efficient resource management [20]. PyECOM enables users to simulate energy flows within a community, considering factors such as energy production, consumption, storage, and distribution. The tool supports various RES and storage systems, BESSs and EVs. Users can model a range of scenarios, such as different levels of RES penetration or alternative storage system configurations [20]. PyECOM incorporates optimization algorithms that assist users in identifying the most efficient configurations for their energy community. These algorithms can be tailored to various objectives, such as minimizing energy costs, reducing greenhouse gas emissions, or maximizing the use of local renewable energy. The tool supports a range of approaches, including deterministic, metaheuristic, and stochastic models [6], [20]. Furthermore, PyECOM can perform economic analysis to evaluate the financial viability of different community energy setups, it also includes modules for assessing the environmental impact of various energy configurations, focusing on carbon footprint and other key metrics [20]. PyECOM is user-friendly, with interfaces that allow users to input data, run simulations, and analyse results without needing deep technical expertise. It offers scalability and versatility, since is suitable for energy communities of all sizes, from microgrids to large urban areas. It also integrates with other energy modelling tools and supports various data formats for easy collaboration and sharing [20].

2.3.1 Solution architecture

The energy community management strategy, based on the PyECOM tool, is presented in Figure 1 and Figure 2. The architecture is depicted in two figures primarily because three methods are implemented. The difference between these methods lies in the type of input data used for load and production in each method. Method 1 (Figure 1) utilizes data from a forecasting module, Method 2 (Figure 1) relies on real-time data, and Method 3 (Figure 2) combines both forecasting and real-time information.
More details about the three methods implemented are described below:

- Methods 1 and 2: The core of this architecture is the PyECOM tool, which incorporates constraints related to the operation of EVs, PV systems, BESS, and CSs. PyECOM receives input data about technical limits of EVs, CSs, and BESS. It is important to note that the input data related to load and production can be derived from a forecasting module (when Method 1 is applied) or from a module with real-time information (when Method 2 is applied). Finally, the output will consist of control commands to be executed on the EVs, batteries, and controllable loads, aiming to optimize energy resources, reduce energy bills, and maximize the utilization of RESs within the energy community. The comparison between Method 1 and Method 2 allows an evaluation of the errors introduced by the forecasting. Method 2 can be seen as the ideal one considering that the forecasting is perfect, i.e., equal to real measurements.

- Method 3: The core architecture, input data about EVs, battery and CSs limits, and control outputs remain consistent. What changes are the input data and how they are processed, as this method involves a step-by-step combination of information from the forecasting module and the real-time data module. Method 3 also considers the scheduling obtained in Method 1. Each step corresponds to an optimization process, which in this case is one hour resolution with one day horizon. Initially, in Step 1, at the start of the optimization (Hour 1), only forecasting data is used. At Hour 2, real-time data is applied for the first hour, while the data from Hour 2 to the end of the horizon (Hour 24) comes from the forecasting module. At Hour 3, real-time data is used for the first two hours, with the remaining hours still relying on the forecast, and this pattern continues incrementally for each subsequent hour, as can be seen in Figure 2. It is important to mention that the forecast values are adjusted considering the errors between the measured values and the forecast ones.

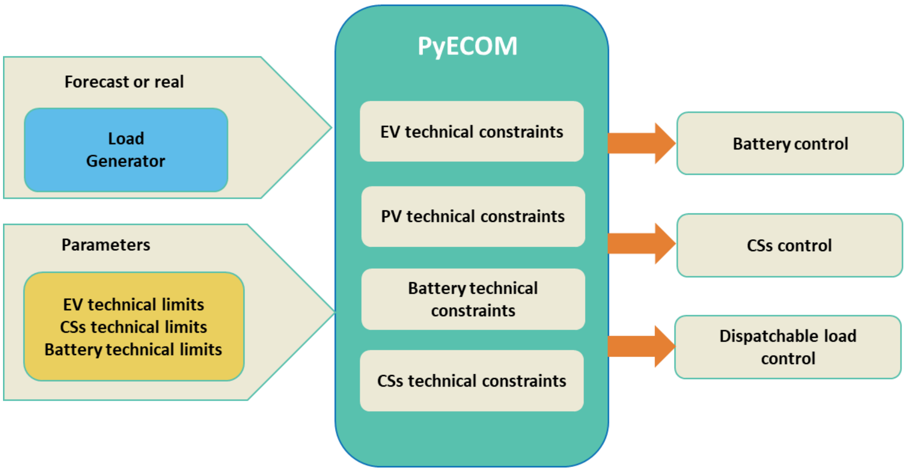

Figure 1 – Energy community management system architecture based on the PyECOM tool, Method 1 and Method 2.

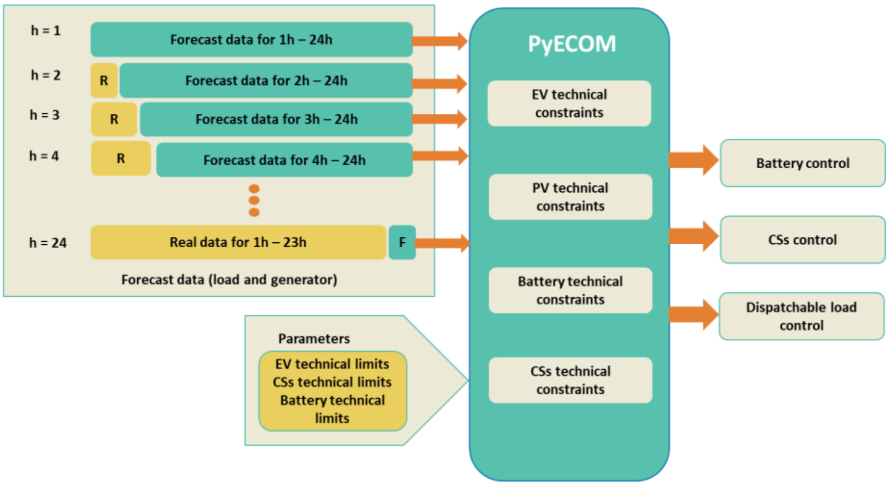

Figure 2 – Energy community management system architecture based on the PyECOM tool, Method 3.

Another important aspect of PyECOM is that it contains components that make it adaptable for use as a foundation to implement optimizations based on deterministic, metaheuristic, and stochastic models. These models are described below in more detail.

2.3.2 Deterministic models

The integration of EVs into energy community systems has become a significant focus area in the context of the broader transition to renewable energy. Deterministic optimization models are crucial in designing and managing these systems, due to their ability to provide precise solutions based on a set of known inputs [21]. The advantage of deterministic models relies on the fact that all input parameters are known with certainty. These models are extensively employed in energy systems to optimize various components, including energy production, distribution, and consumption, with a particular focus on EVs. The objective functions within these models are generally designed to minimize costs, enhance efficiency, or balance supply and demand. In the context of EVs, the objectives may include minimizing charging costs, maximizing the utilization of renewable energy, or reducing dependency on the grid. In the management of energy communities decentralized systems where energy is produced, stored, and consumed locally, EVs serve a dual role as both energy consumers and potential storage units. Through the implementation of V2G technology, EVs can discharge energy back into the system. Additionally, deterministic models leverage known load profiles for forecasting energy demand, including the specific requirements associated with EV charging [21]. Moreover, typical constrains considered for energy community management based on deterministic model are related to operational limits of the network system, PV production, wind turbine production, BESS, EVs, CSs, controllable loads, generators, among others.
The deterministic model implemented in PyECOM is guided by a minimization objective function (OF), as detailed in equations (1)–(6). The overall OF, presented in Equation (Eq.) (1) incorporates five key components: generators, represented by Eq. (2), loads, represented by Eq. (3), BESS by Eq. (4), EVs by Eq. (5), and system by Eq. (6).

$$\min f = G + L + B + EV + S \tag{1}$$

$$G = \sum_{t\in T}\sum_{g\in G}(P_{t,g}^{G+}\Delta_t C_{t,g}^{G+} + P_{t,g}^{G-}\Delta_t C_{t,g}^{G-}) \tag{2}$$

$$L = \sum_{t\in T}\sum_{l\in L}(L_{t,l}^{r}\Delta_t C_{t,l}^{r} + L_{t,l}^{c}\Delta_t C_{t,l}^{c} + L_{t,l}^{ENS}\Delta_t C_{t,l}^{ENS}) \tag{3}$$

$$B = \sum_{t\in T}\sum_{g\in G}(P_{t,b}^{B+}\Delta_t C_{t,b}^{B+} + P_{t,b}^{B-}\Delta_t C_{t,b}^{B-} + (P_{t,b}^{relaxB+})^2 m + (P_{t,b}^{relaxB-})^2 m + E_{t,b}^{Brelax} M) \tag{4}$$

$$EV = \sum_{t\in T}\sum_{ev\in EV}(P_{t,ev}^{EV+}\Delta_t C_{t,ev}^{EV+} + P_{t,ev}^{EV-}\Delta_t C_{t,ev}^{EV-} + (P_{t,ev}^{relaxEV+})^2 m + (P_{t,ev}^{relaxEV-})^2 m + E_{t,ev}^{EVrelax} M) \tag{5}$$

$$S = \sum_{t\in T}(P_t^{Imp}\Delta_t C_t^{buy} - P_t^{Exp}\Delta_t C_t^{sell} + P_t^{Imprelax} p) \tag{6}$$

Each expression is associated with the energy generated or consumed by each component and the corresponding energy prices, in which Δ_t represents the time interval. Thus, $P_{t,g}^{G+}$ and $P_{t,g}^{G-}$ represents the energy imported/exported by the generators, with $C_{t,g}^{G+}$ and $C_{t,g}^{G-}$ denoting the associated costs. $L_{t,l}^{r}$, $L_{t,l}^{c}$, and $L_{t,l}^{ENS}$refer to the energy that can be reduced, curtailed, or even not supplied for the system's loads, while $C_{t,l}^{r}$, $C_{t,l}^{c}$ and $C_{t,l}^{ENS}$ represents the prices associated with each, respectively. $P_{t,b}^{B+}$ and $P_{t,b}^{B-}$ denotes the energy charged/discharged by the batteries, with $C_{t,b}^{B+}$ and $C_{t,b}^{B-}$ corresponding to the related prices. In the case of EVs, $P_{t,ev}^{EV+}$and $P_{t,ev}^{EV-}$represent the energy charged/discharged by them, while $C_{t,ev}^{EV+}$ and $C_{t,ev}^{EV-}$ indicate the associated prices. For the system, $P_{t}^{Imp}$and P_{t}^{Exp}represent the import and exported power, respective, while C_{t}^{buy} and C_{t}^{Sell} indicate the associated prices. The OF is subject to operational constraints related to EVs, CSs, BESS, generators (including PVs), main grid constrains related to import and export power, and energy balance in the system.

2.3.3 Metaheuristic models

Metaheuristic-based optimization models are increasingly being used for the integration of EVs into energy communities. These models are crucial in addressing the complexities and uncertainties associated with RES, demand response, and EV charging behaviours [6]. Some of the most popular are the genetic algorithm (GA) [22], Differential Evolution (DE) [6], Particle Swarm Optimization (PSO) [23], the Mountain Gazelle Optimizer (MGO) [6], the Dandelion Optimizer (DO) [6], and the Hybrid Adaptive Differential Evolution with Decay Function (HyDE-DF) [6], among others.

In the context of energy communities, GA is used to optimize the scheduling of EV charging and discharging, ensuring that the demand is met while minimizing costs and emissions. It is particularly effective in handling the non-linear and non-convex nature of EV integration problems. DE is effective in continuous optimization problems and is used in EV integration to optimize charging schedules and grid interactions. It has been shown to be robust in finding global optima in complex, high-dimensional spaces. PSO, inspired by the social behaviour of birds flocking or fish schooling, is used for optimizing multi-objective functions in EV integration, such as minimizing energy costs while maximizing the use of RESs. PSO is known for its ability to converge quickly to a good solution, making it suitable for real-time application. MGO and DO could be used to optimize various aspects of EV design and operation, such as battery management systems, energy efficiency, and the logistics of CSs placement, moreover, by simulating the dispersal and refinement process of dandelion seeds, DO optimizer could help in finding optimal solutions in these complex, multidimensional problems. HyDE-DF can be applied to various aspects of EV technology, particularly in optimizing complex systems such as battery management, energy efficiency, and the design of charging infrastructure. For example, HyDE-DF could be used to fine-tune the parameters of battery management systems to extend battery life and improve performance, or to optimize the placement and operation of CSs in a smart grid environment. The metaheuristic-based model implemented with PyECOM [6] is driven by a minimization OF as outlined in Eq. (7) – (9). The overall OF, as presented in Eq. (7), resembles that of the deterministic model, with the primary differences arising in the expressions related to EVs and BESS. Specifically, each component of the OF corresponds to the following: generators, represented by Eq. (2), loads by Eq. (3), BESS by Eq. (8), and EVs by Eq. (9).

$$\min f = G + L + B + EV + S \tag{7}$$

$$B = \sum_{t \in T} \sum_{g \in G} \left(P_{t,b}^{B+} \Delta_t C_{t,b}^{B+} + P_{t,b}^{B-} \Delta_t C_{t,b}^{B-} + \left(P_{t,b}^{B+}\right)^2 m + E_{t,b}^{Brelax} M\right) \tag{8}$$

$$EV = \sum_{t \in T} \sum_{ev \in EV} \left(P_{t,ev}^{EV+} \Delta_t C_{t,ev}^{EV+} + P_{t,ev}^{EV-} \Delta_t C_{t,ev}^{EV-} + \left(P_{t,ev}^{EV+}\right)^2 m + E_{t,ev}^{EVrelax} M\right) \tag{9}$$

2.3.4 Stochastic models

The integration of RES introduces significant uncertainty due to their intermittent nature. Stochastic models can optimize the scheduling of EV charging/discharging while accounting for these uncertainties [24]. The stochastic-based model implemented with PyECOM is driven by a minimization OF, as outlined in equations (10) – (12). The OF $\min f$ of stochastic model is given as the sum of two components F^{DA} and F^{RT}, representing costs associated with day-ahead and real-time operations, respectively. In this case, the day-ahead component allows to make decisions to plan the next day's operation based on forecasts and expected conditions. On the other hand, real-time component represents the adjustments made based on probable scenarios, that are in discrepancies with day-ahead components. The proposed model identifies the most cost-effective strategy for meeting anticipated demand by optimally scheduling generation, imports, loads, down, and up reserves. Hence, the up reserves are designed to increase the generation capacity or decrease load when there is a shortage of power in the system. This might occur due to unexpected increases in demand or failures in generation units. Conversely, down reserves serve to decrease generation or increase demand when there is an excess of power in the system. This surplus can occur when demand is lower than forecasted or when variable RES, such as wind or solar, produce more energy than anticipated.

Within the framework of stochastic programming, this model is classified as a two-stage stochastic model. The first stage corresponds to the day-ahead component, while the second stage addresses the real-time component, where the model explicitly incorporates uncertainties in demand and generation availability. This is reflected in the scenarios (w), which are weighted by their probabilities (π_w). Note that the OF is to minimize the total expected cost of operating the energy community, as is shown in Eq. (10). The variables R_t^{UPimp} and $R_t^{Downimp}$ represent the up and down power reserve requirements for the main grid, necessary to increase or decrease output to meet the anticipated demand. The corresponding costs for each energy reserve are denoted as C_t^{UPimp} and $C_t^{Downimp}$, respectively. The variables $R_{t,s}^{UPbess}$ and $R_{t,s}^{Downbess}$ represent the up and down power reserve requirements offered by the BESSs, necessary to increase or decrease output to meet the anticipated demand. The corresponding costs for each energy reserve are denoted as $C_{t,s}^{UPbess}$ and $C_{t,s}^{Downbess}$, respectively. The variables $r_{t,w}^{UPimp}$ and $r_{t,w}^{Downimp}$ were introduced to define the up and down reserves from the grid import power that can be offered considering different scenarios.

$$\min f = F^{DA} + F^{RT} \tag{10}$$

$$\begin{aligned} F^{DA} = & \sum_{t=1}^{T} R_t^{UPimp} \Delta_t C_t^{UPimp} + R_t^{Downimp} \Delta_t C_t^{Downimp} \\ & + \sum_{t=1}^{T} \sum_{s=1}^{S} R_{t,s}^{UPbess} \Delta_t C_{t,s}^{UPbess} + R_{t,s}^{Downbess} \Delta_t C_{t,s}^{Downbess} \end{aligned} \tag{11}$$

$$F^{RT} = \sum_{w}^{nW} \pi_{(w)} \times \tag{12}$$

$$
\left[\begin{array}{c}
\sum_{t=1}^{T}\sum_{w=1}^{W} P_t^{Imp}\Delta_t C_t^{buy} - P_t^{Exp}\Delta_t C_t^{sell} + P_t^{Imprelax}p + r_{t,w}^{UPimp} c_t^{buy} + r_{t,w}^{Downimp} c_t^{sell} \\
+\sum_{t=1}^{T}\sum_{g=1}^{G}(P_{t,g,w}^{G}\Delta_t C_{t,g}^{G}) \\
+\sum_{t=1}^{T}\sum_{b=1}^{nB} P_{t,b}^{Dch}\Delta_t\, C_{t,b}^{Dch} + r_{t,s,w}^{UPbess}\Delta_t c_{t,s}^{UPbess} + r_{t,s,w}^{Downbess}\Delta_t c_{t,s}^{Downbess} + \left(P_{t,b}^{relaxB-}\right)^2 m + E_{t,b}^{Brelax}M) \\
+\sum_{t=1}^{T}\sum_{e=1}^{nEV} P_{t,ev}^{EV}\,\Delta_t C_{t,ev,w}^{EV+} + \left(P_{t,ev,w}^{relaxEV-}\right)^2 m + E_{t,ev,w}^{EVrelax}M) \\
+\sum_{t=1}^{T}\sum_{l=1}^{L} L_{t,l}^{r}\,\Delta_t C_{t,l}^{r} + L_{t,l}^{c}\,\Delta_t C_{t,l}^{c} + L_{t,l}^{ENS}\,\Delta_t C_{t,l}^{ENS}
\end{array}\right]
$$

3 Simulation Results

This section presents the simulation results, highlighting key features of the proposed Energy Community Management System. Subsection 3.1 details the model assumptions for the PyECOM-based deterministic, metaheuristic, and stochastic models. Subsection 3.2 discusses the primary findings related PyECOM-based deterministic, metaheuristic, and stochastic models.

3.1 Model assumptions for deterministic and metaheuristic models

To validate the energy community management approach proposed in this document, for deterministic and metaheuristic models, one use case (UC) have been analysed. The UC represents an energy community comprising sixteen residential households and four small commercial buildings, twenty BESS, sixteen EVSE units, thirty-two EVs, twenty Generators (considered as PV units), and the distribution network technical limits, considering a local transformer with 100kW of nominal capacity with a usage limitation of 80%, as shown, in a representative way, by Figure 3. For each BESS, charging and discharging efficiencies within 0.95 and 0.96 were assumed. For the EVSEs, charging and discharging efficiencies of 0.95 were also considered. However, as illustrated in Figure 3, it was assumed that some EVSEs are equipped with V2G technology, for this UC, ten EVSEs were considered. Regarding the EVs, it was assumed that several of the EVs are equipped with V2G technology, in this case eighteen EVs. These V2G-enabled vehicles have both charging and discharging efficiencies set to 0.98. On the other hand, vehicles without V2G technology have a charging efficiency of 0.98 and a discharging efficiency of 1.00. It is important to note that, since there are more cars than EVSEs, the mathematical model includes input data specifying the connection place of each EVs. This ensures that only one car is connected to each EVSE at any given time.
For the metaheuristic model were considered the DO and HyDE-DF algorithms. Each algorithm requires hyperparameters to run correctly, more details can be found in [6]. The hyperparameters of each of them are detailed in Table 1, in which pop represents the population considered, F_{weight} is the function weight, and F_{CR} is the crossover value.

Table 1: Algorithms hyperparameters settings

Algorithm	Parameters
HyDE-DF	$pop = 20, F_{weight} = 0.5, F_{CR} = 0.3$
DO	$pop = 20$

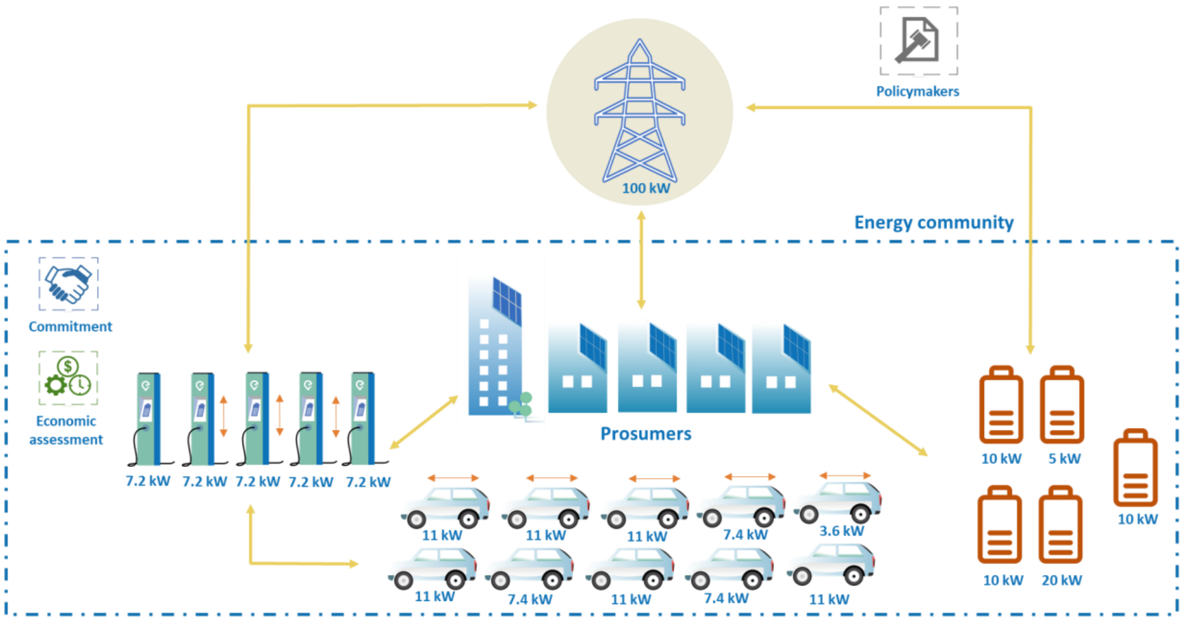

Figure 3 – Energy community details for UC

The input data related to Generators for the Method 1 (Forecasting data) and Method 2 (Real data) are illustrated by Figure 4. On the other hand, the input data about the load consumption used for Method 1 (Forecasting data) and Method 2 (Real data) are illustrated by Figure 5. The analysis of the forecasting data for generator profiles indicates that the four commercial buildings exhibit forecasted peaks of 7.5kW, 11.75kW, 16.09kW, and 20.6kW, while the residential houses display peak productions of less than 3.6kW. In contrast, the real data reveal that the generator profiles for these buildings have slightly higher peak power production than the forecasts, with observed peaks of 9.3kW, 14.4kW, 19.8kW, and 25.4kW. Conversely, the residential houses demonstrate lower peak productions in real data, with values under 2.8kW, which are smaller than the forecasted data.
Related to the load consumption, for the forecasting data, the profiles shows that the four commercial buildings exhibit peak consumptions power of 31.23kW, 24.3kW, 17.7kW, and 11.41kW, while the residential houses display peak power consumption less than 4.7kW. In contrast, the real data reveal that the peak consumption power for these buildings have slightly higher peak consumption than the forecasts, with observed peaks of 40.29kW, 31.33kW, 22.88kW, and 14.73kW. On the other hand, the residential houses demonstrate higher peak productions in real data, with values under 5.8kW, which are higher than the forecasted data. Moreover, for these profiles, the data on real-time information is sourced from a database containing actual records from several residential houses on a Portuguese island, hence the values of four houses were adjusted to reflect power consumption and generation levels typical of four commercials buildings [25]. The forecasting data is derived from a forecasting database, which uses input data based on the actual records from the same houses on a Portuguese island [25]. Data related to energy prices was taken from [26].

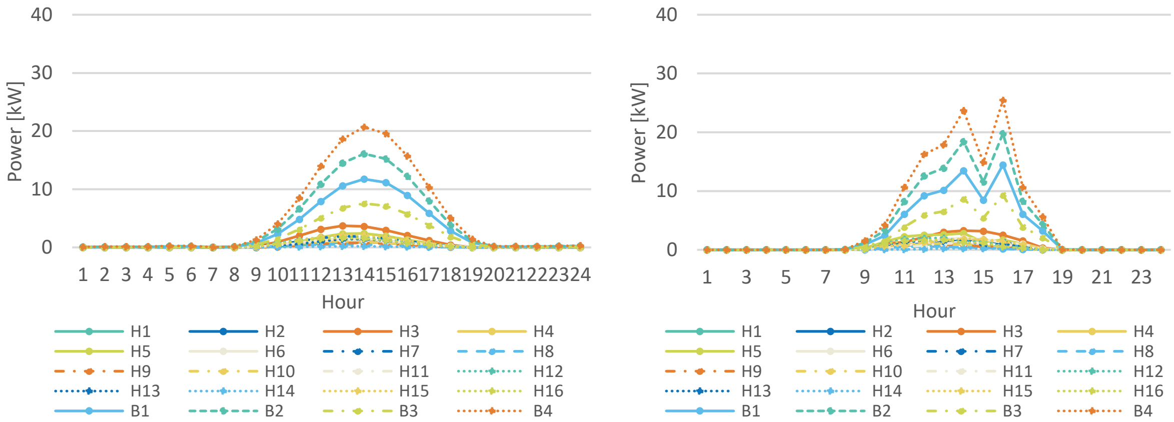

Figure 4 – Generators profiles for Method 1, forecasting data (left side), Method 2, real data (right side) for UC

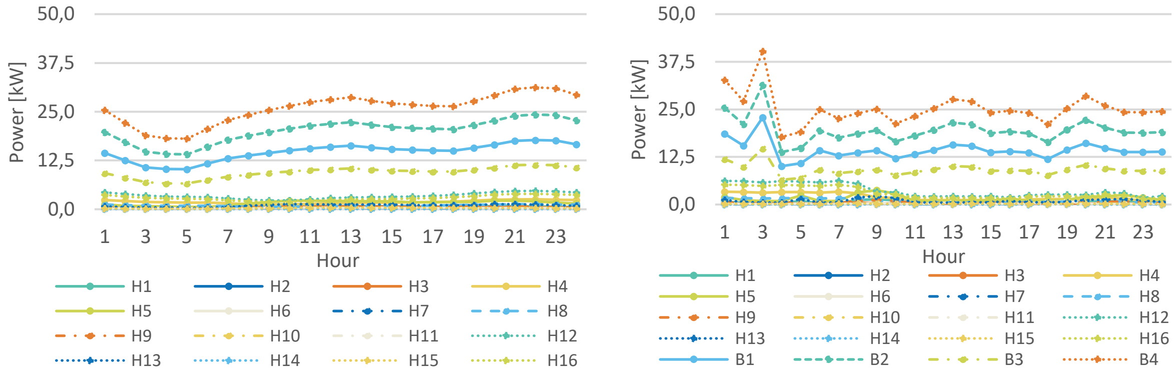

Figure 5 – Load consumption for Method 1, forecasting data (left side), Method 2, real data (right side) for UC

3.2 Model assumptions for stochastic model

To validate the energy community management approach proposed in this document, the UC analyzed for the deterministic model, as depicted in Figure 3, was also considered within the stochastic model considerations. Moreover, five distributions of probability for generators and load consumption profiles were considered into Method 1, as shown, in a representative way, for one commercial building data in Figure 6 and one household in Figure 7. To validate the stochastic model's performance in scheduling reserves, the reserves were programmed based on grid imported power and BESS managed power. The scenario combination resulted in 25 distinct cases, each with a 0.04 probability.

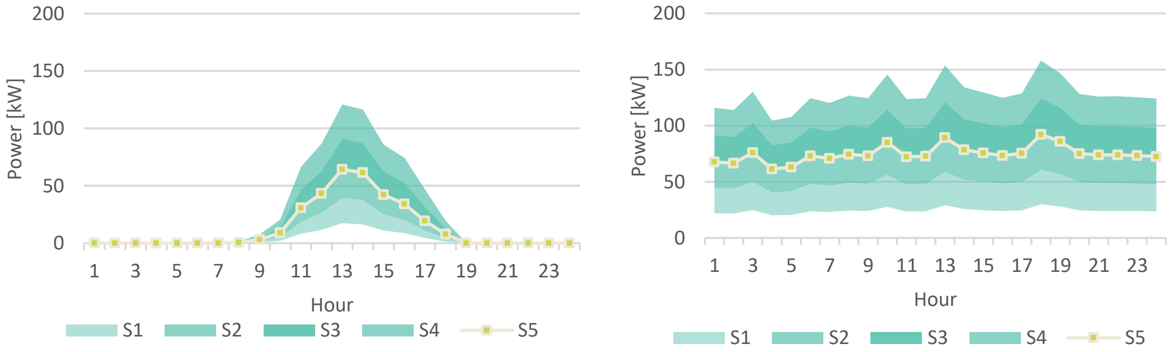

Figure 6 – Generators distribution probability (left side) and load distribution probability (right side) for Method 1, considering a representative commercial building.

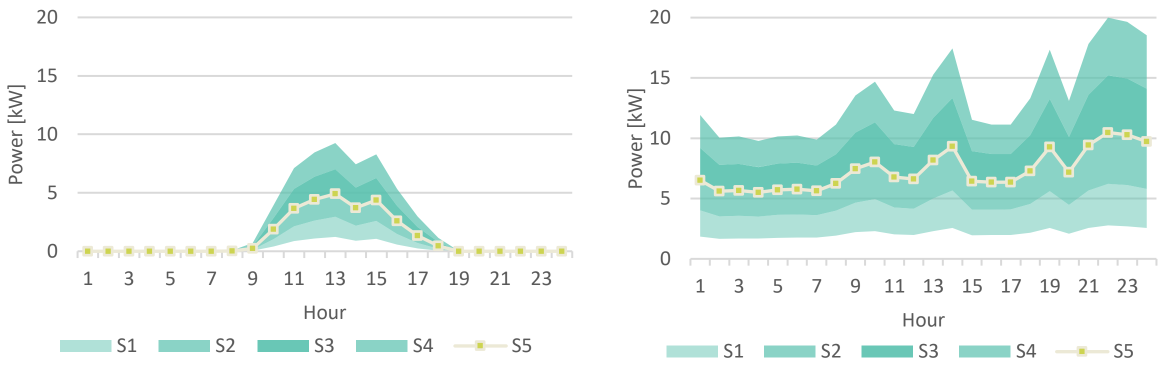

Figure 7 – Generators distribution probability (left side) and load distribution probability (right side) for Method 1, considering a representative household.

To generate probabilistic forecasts of generators and load consumption profiles, we employed data from the same households on a Portuguese island, previously utilized for the deterministic model [25]. The Quantile Regression method [27] was implemented. The process began with data pre-processing, where the raw datasets were resampled from a 15-minute to a 1-hour resolution, and missing values were handled using forward filling. For feature engineering, date-time features were extracted, and lag features were created for the target variables to capture temporal dependencies. This included generating lag features for 1, 2, and 3 days prior, which were crucial for capturing time-dependent patterns. The features influencing solar power included solar radiation metrics like Global Horizontal Irradiance (GHI) and lagged values of solar power itself. For load, the features included not only lagged load values but also solar power generation. These features were then used as inputs for the forecasting model. Quantile Regression was selected as the forecasting method, allowing the estimation of different quantiles: 10th, 30th, 50th, 70th, and 90th for PV power, and 40th, 45th, 50th, 55th, and 60th for load. The model was trained on historical data from December 7th, 2018, to November 5th, 2019, and forecasts were produced for the next day, November 6th, 2019.

3.3 Energy community management results

3.3.1 Main results for deterministic model

The main results of the energy community management, based on the deterministic model using PyECOM for the three methods considered, are presented in Figure 8 – Figure 11. For Method 1, as shown in Figure 8 (left side), the peak import power reached 80kW, which corresponds to the maximum capacity of the main transformer. This peak in grid import power decreases at 12h00, coinciding with the start of increased generator power production. The peak EV discharging power is managed to occur at 19h00 with a discharge of 10.74 kW, and at 21h00 with 16.34 kW. Similarly, the BESS discharging power is scheduled for 20h00 reaching 25.66 kW, and 22h00 reaching 30.38 kW. These timings are intended to support periods of higher load consumption (19h00 – 23h00), in which the peak load consumption occurs at 22h00 with 103.93kW. Moreover, the algorithm manages the discharge of both BESS and EV during periods of low power demand, specifically when generator power is unavailable. The BESS primarily discharge between 01h00 and 3h00 to meet the changing requirements of the EVs (as illustrated on both sides of Figure 8), while the EVs discharge between 07h00 – 11h00 to support the community's load consumption (see both sides of Figure 8). Finally, during periods of elevated generation power (13h00 – 15h00), neither the BESS nor the EVs are discharged, as the load consumption is met by the grid import power in conjunction with the generation production. Moreover, the BESSs and EVs are encouraged to take advantage of the solar production by maximising their charging power between 13h00 – 15h00, as shown in Figure 8 (right side). Hence, the peak of BESS charging power occurs at 14h00, reaching 50.28 kW, while the EVs achieve their peak consumption at 17h00 with 49.35 kW. In the case of the EVs, due to the non-stationary nature of their batteries (which are dependent on user behaviour), the algorithm can efficiently utilize the generator power production when users return to the charging points around 17h00. Furthermore, in this UC scenario, using Method 1, from the production point of view there is no observed load reduction, load curtailment, or load energy not supplied (ENS). On the other hand, in terms of consumption, there is no grid export power. Moreover, for this operation day, the total grid import energy was 1896.77kWh, the total BESS discharging energy was 156.64kWh, the total EV discharging energy was 49.68kWh, and the total generators energy production was 462.25kWh, in terms of total consumption, the EVs consumed a total 385.08kWh, the total BESS charging energy was 139.45kWh, and the total load consumption achieved 2040.80kWh at the end of the operation day.

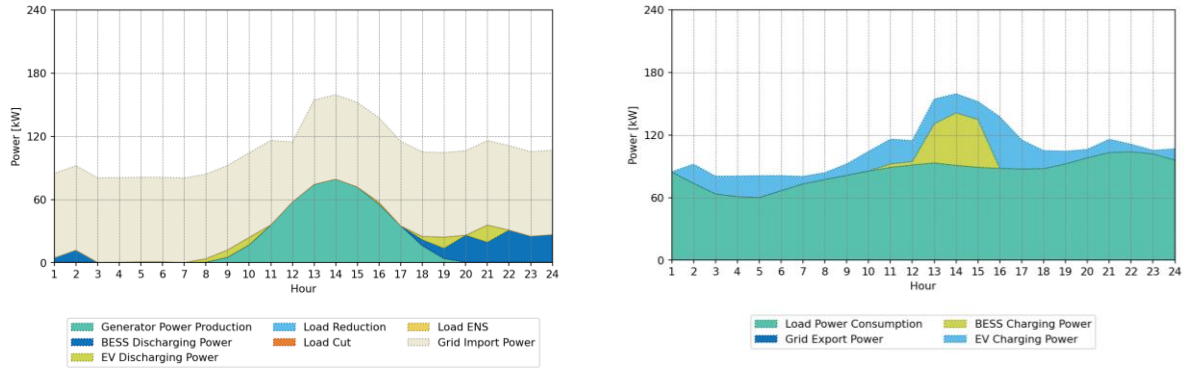

Figure 8 – Production (left side) and Consumption (right side) results for deterministic model, Method 1

Figure 9 presents the results for production (left side) and consumption (right side) under Method 2. When comparing Method 1 with Method 2, it is evident that under the analysis of real data, where there was a 7.0% increase in generator availability on this day of operation, the algorithm takes advantage of this to increase the charging of both BESS and EV, as shown in Figure 9. Consequently, the BESS peak charging power occurs at 13h00 reaching 54.69 kW, while the EVs reach their peak charging power at 16h00 with 46.07 kW. This represents an increase of 9.0% and 6.7%, respectively, compared to Method 1. Regarding production, it can be observed that due to the increased availability of generators, Method 2 exhibits more periods with reduced grid import power, particularly at 11h00, 12h00, and 14h00. The greatest reduction occurs at 12h00 with only 17.42kW being imported. During this time, the system's total load (77.20 kW), considering both normal loads and EVs) is primarily supported by the generators, providing 63.44kW and with a small contribution from the EVs with 3.6kW. It is important to note that some vehicles are discharged while others are charged, always within their operational limits. On the other hand, like Method 1, in Method 2, the BESSs and EVs are also managed by the algorithm to help meet the system's load, particularly during periods of higher demand. Between 1h00 – 4h00, the BESSs are primarily utilized to support the grid, even reaching their peak discharge power of 59.42 kW at 3h00. The EVs, in turn, are used between 6h00 – 12h00 to complement the grid, notably after the BESS have been heavily utilized. The EVs reach their peak discharge power of 22kW at 22h00, supporting the grid during hours when community users are expected to have returned to the EVSEs. Regarding consumption, the algorithm leverages the increased availability of generators to enhance the charging of BESS and EVs during peak production hours (11h00 – 17h00), thereby improving the community's utilization of sustainable resources. Finally, on this operational day, total grid import energy amounted to 1823.40kWh, while total BESS discharging energy reached 194.69kWh, the total EV discharging energy was 89.56kWh, and generator energy production was 496.25kWh. As a result, under this method incorporating real-time data, generator power production exhibited a 7% increase compared to Method 1. Furthermore, as with Method 1, Method 2 showed no load reduction, load cut, or load ENS. In terms of consumption, this method, resulted in total EV consumption of 426.44kWh, with a total BESS charging energy of 194.69kWh. The overall load consumption reached 1992.50kWh.

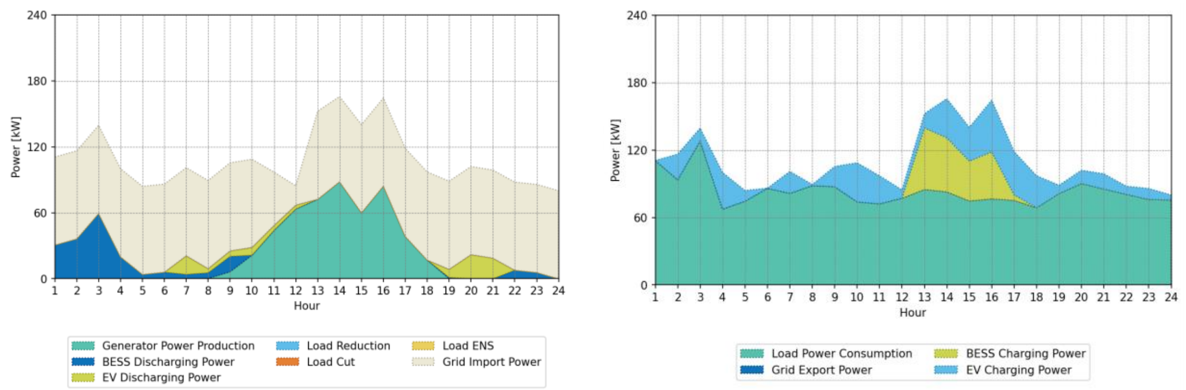

Figure 9 – Production (left side) and Consumption (right side) results for deterministic model, Method 2

Figure 10 shows production (left side) and consumption (right side) results for Method 3. For this method, due to its inherent uncertainties, which combines real and forecasted data, it was not possible to avoid load reduction, having its peak reduction (64.03kW) at 3h00, as can be seen in Figure 10 (left side). In terms of consumption, EVs have their peak power charging (49.83kW) at 16h00, while BESSs have their peak power charging of 68.08kW at 14h00, like the EVs, taking advantage of the power production from generators, as can be seen in Figure 10 (right side). At 16h00, this method achieved the greatest reduction in grid import power, driven by the availability of generator power and a small contribution from EVs, which provided 1.23kW of discharging power. The algorithm also manages BESSs and EVs to support the system's load, particularly during periods of high demand and when generator power is unavailable. From 1h00 – 3h00 and 20h00 – 24h00, BESSs are primarily utilized to assist the grid, reaching their maximum discharge power of 33.75kW at 22h00. EVs, on the other hand, are most active between 18h00 and 22h00, complementing the grid and achieving a peak discharge power of 15.41kW at 21h00. This support aligns with the expected return of community users to the EVSEs during these hours.

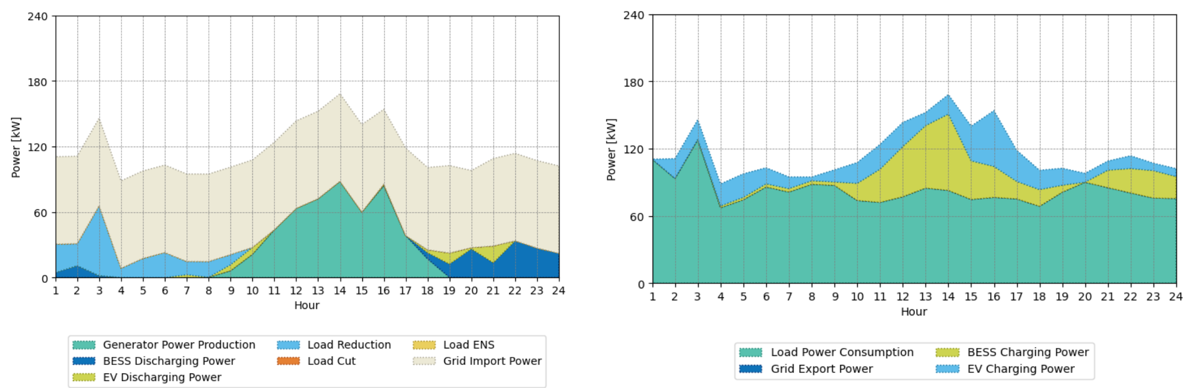

Figure 10 – Production (left side) and Consumption (right side) results for deterministic model, Method 3

Due to the uncertainties inherent in this method, the community's power consumption was adjusted through load reduction and load cut. As a result, the system's net consumption load is presented in Figure 11. Thus, it is possible to observe how the load power consumption curve is adjusted, with the peaks of controllable loads (EVs and BESSs) aligning with the peaks of load reduction and load cut.

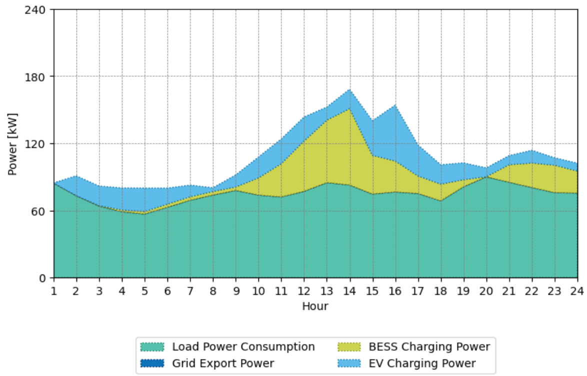

Figure 11 – Net consumption results for deterministic model, Method 3

On this operational day, total grid import energy amounted to 1920kWh, while total BESS discharging energy reached 263.64kWh, EVs discharging energy was 23.47kWh, generator energy production was 496.37kWh, load energy reduction was 762.06Wh, with 136.16kWh of load cut, without load ENS. In terms of consumption, resulted in total EV consumption of 388.25kWh, 408.74kWh of BESS energy consumption, and the overall load consumption reached 1797.09kWh.
Table 2 provides a summary of the energy produced and consumed for each method in the UC analysed for the deterministic model, in which the final load energy consumption includes the load power consumption, the BESSs, and the EVs charging power. As is evident, due to uncertainties, Method 3 is unable to prevent load reduction. However, the EVs were managed to charge 9% less compared to Method 1, while the BESS were managed to charge 25% less than in Method 1.

Table 2: Summary of the energy production and consumption (kWh) for the three methods of the deterministic model

Method	Energy Imported	Final Load energy consumption	Community Load Energy consumption	Energy reduction	Energy cut	Energy ENS	Generator's energy	BESS and EVs Energy discharging	Energy exported
Method 1	1,896.77	2,565.34	2,040.80	0.00	0.00	0.00	462.24	206.33	0.00
Method 2	1,823.40	2,603.37	1,992.50	0.00	0.00	0.00	496.37	283.59	0.00
Method 3	1,894.24	2,594.09	1,992.50	195.40	0.00	0.00	496.37	203.47	0.00

3.3.2 Main results for metaheuristic model

The key outcomes of energy community management, derived from the metaheuristic DO algorithm using PyECOM for the three methods considered, are illustrated in Figure 12 – Figure 17. Figure 12 presents the production (left side) and consumption (right side) results for Method 1, utilizing the DO algorithm. As evident from the figure, the DO algorithm demonstrates suboptimal performance, exhibiting load reduction, load cut, and load ENS, and grid export power. The peak discharging power of BESSs (67.12kW) occurs at 2h00, this aiming to help with the total load consumption considering the high EV charging power (79.54kW) at this same period. The DO algorithm does not take advantage of the generator power availability to manage the BESSs and EVs charging power (see Figure 12, right side). On this operational day, the total grid import reached 1,345.18kWh, with a BESS discharge of 791.35kWh and EV discharge energy of 35.77kWh. Load management contributed to an overall energy reduction of 57.95kWh, with 24.89kWh from load curt and 4.54kWh from load ENS. Furthermore, the total energy used on-site from generators amounted to 414.55Wh. On the consumption side, EV charging accounted for 309.38kWh, while BESS charging totalled 274.06kWh. The overall load consumption was 1,953.42kWh, with 47.69kWh exported to the grid by the end of the day.

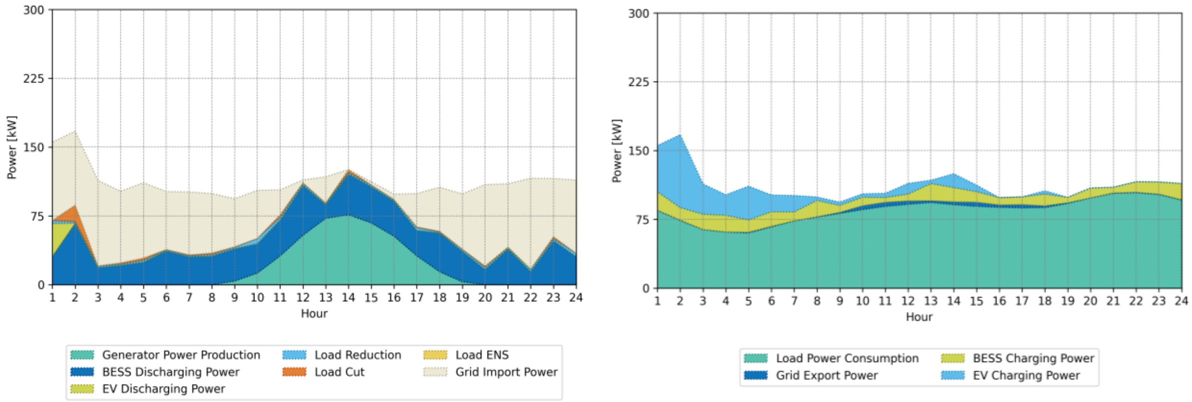

Figure 12 – Production (left side) and Consumption (right side) results for metaheuristic model (DO), Method 1

Due to the poor performance of the DO algorithm, the community's power consumption was adjusted through load reduction, load cut, and load ENS. As a result, the system's net consumption load, for Method 1, is presented in Figure 13. Thus, it is possible to observe how the load power consumption curve is adjusted aligning with the peaks of load reduction, load cut, and load ENS.

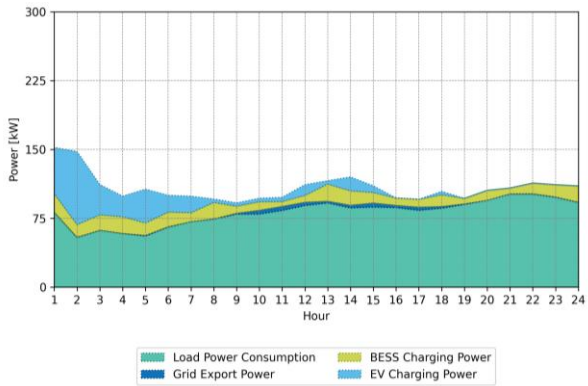

Figure 13 – Net consumption results for metaheuristic model (DO) Method 1

Figure 14 presents the production (left side) and consumption (right side) results for Method 2, utilizing the DO algorithm. As evident from the figure, the DO algorithm under the usage of real time data demonstrates a poor performance, exhibiting a higher load reduction, load ENS, and grid export power when compared to the Method 1. On the other hand, in Method 2, the BESSs discharging power is managed to support the higher load consumption (124.14kW) at 3h00, with a peak discharging power of 79.73kW at the same hour, different from Method 1, in which the BESSs were used to support the EV charging power. Like Method 1, the DO algorithm in Method 2 does not take advantage of the generator power availability to manage the BESSs and EVs charging power (see Figure 14, right side).

On this operational day, the total grid import reached 1,289.75kWh, with a BESS discharge of 779.90kWh and EV discharge energy of 35.97kWh. Load management contributed to an overall energy reduction of 60.71kWh, with 90.28kWh from load curt and 5.73kWh from load ENS. Furthermore, the total energy used on-site by generators amounted to 463.72kWh. On the consumption side, EV charging accounted for 309.96kWh, while BESS charging totalled 357.96kWh. The overall load consumption was 1,835.77kWh, with 32.65kWh exported to the grid by the end of the day.

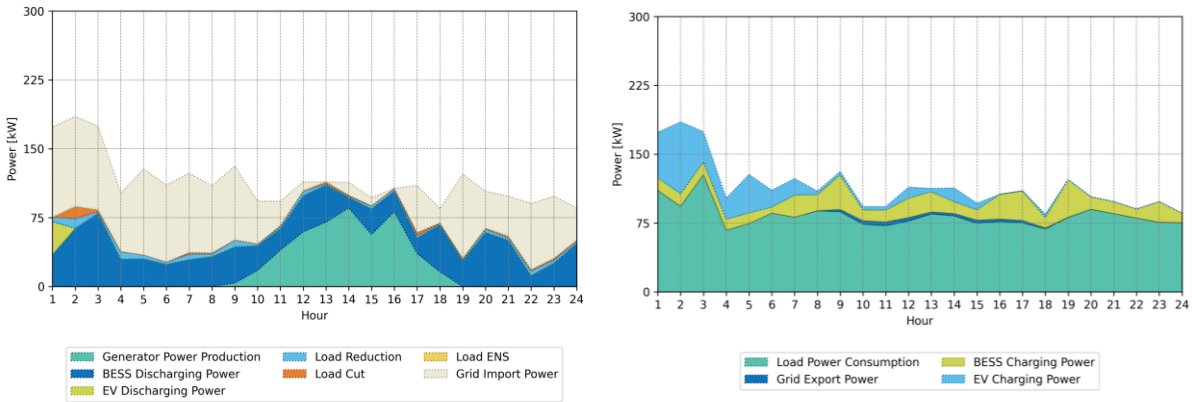

Figure 14 – Production (left side) and Consumption (right side) results for metaheuristic model (DO), Method 2

Due to the poor performance of the DO algorithm, the community's power consumption was adjusted through load reduction, load cut, and load ENS. As a result, the system's net consumption load is presented in Figure 15. Thus, it is possible to observe how the load power consumption curve is adjusted aligning with the peaks of load reduction, load cut, and load ENS.

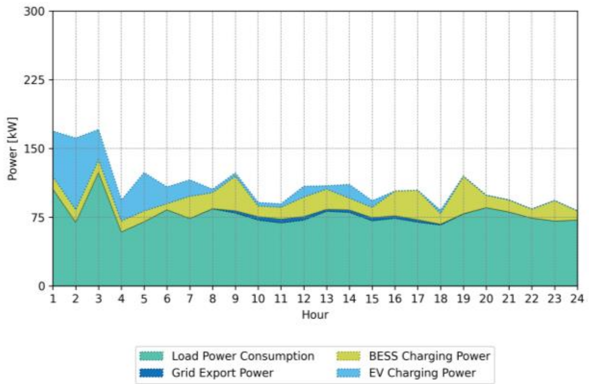

Figure 15 – Net consumption results for metaheuristic model (DO) Method 2

Figure 16 displays the outcomes for energy production (on the left) and consumption (on the right) for Method 3, utilizing the DO algorithm. Although Method 3 considers data uncertainty, it shows no notable advancements in smart energy management for BESS, EVs, and generators when compared to Methods 1 and 2. Challenges such as load reduction, load curtailment, load ENS, and grid export power continue to exist, indicating suboptimal use of the PV units.

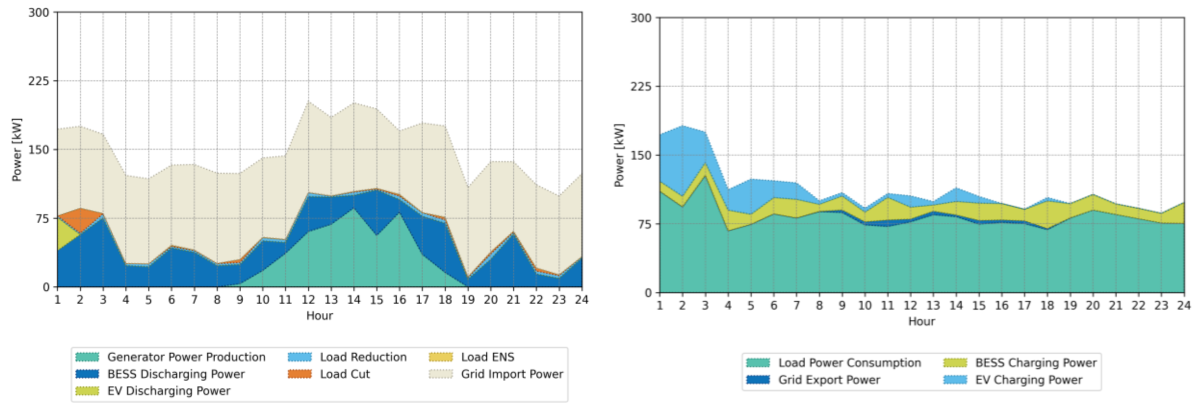

Figure 16 – Production (left side) and Consumption (right side) results for metaheuristic model (DO), Method 3

For this operational day, the total grid import amounted to 2,180.57kWh, with a total BESS discharge of 778.85kWh and EV discharge of 36.42kWh. The total energy reduction was 63.29kWh, including 48.14kWh from load curtailment and 4.88kWh from load ENS. Additionally, the total energy used by the generators reached 462.80kWh. On the consumption side, EVs charged a total of 314.14kWh, while the BESS charging energy totalled 368.89kWh. The total load consumption amounted to 1,876.18kWh, with 33.56kWh exported back to the grid by the end of the day. Among the three methods, this approach performed the worst in terms of energy balance management for the energy community, importing 26.01% more energy than necessary to meet the total load consumption. This result is expected, as this method contends with highly uncertain and mixed input data from both forecasting and real-time sources.

Due to the poor performance of the DO algorithm for method 3, the community's power consumption was adjusted through load reduction, load cut, and load ENS. As a result, the system's net consumption load is presented in Figure 17. Thus, it is possible to observe how the load power consumption curve is adjusted aligning with the peaks of load reduction, load cut, and load ENS.

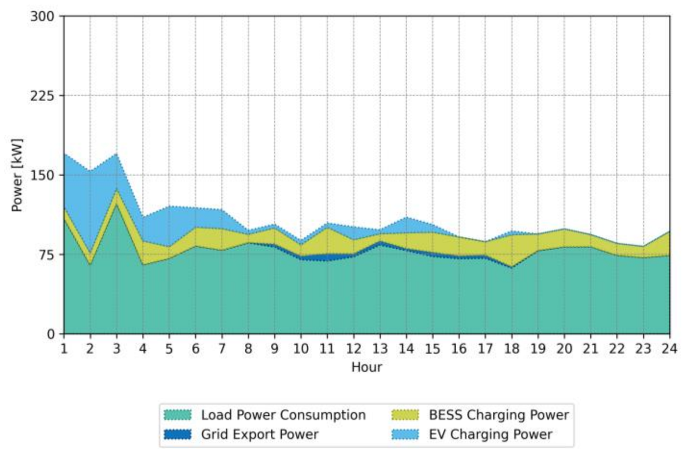

Figure 17 – Net consumption results for metaheuristic model (DO), Method 3

Table 3 summarizes the energy production and consumption for each method in the UC analysis using the DO algorithm. As indicated, this algorithm, like HYDE-DF, is unable to effectively manage the energy community to prevent load curtailment, load reduction, and load ENS across all three methods.

Additionally, inefficient utilization of the generators is observed, along with the importation of more energy than necessary to meet the system's load demand, particularly in Method 3.

Table 3: Summary of the energy production and consumption (kWh) for the three methods of DO algorithm

Method	Energy Imported	Final Load energy consumption	Community Load Energy consumption	Energy reduction	Energy cut	Energy ENS	Generators energy	BESS and EVs Energy discharging	Energy exported
Method 1	1,345.17	2,536.87	1,953.42	57.95	24.89	4.54	414.55	827.12	47.69
Method 2	1,289.76	2,503.11	1,835.77	60.71	90.28	5.73	463.72	815.87	32.64
Method 3	2,180.57	2,559.21	1,876.18	63.29	48.14	4.88	462.80	815.27	33.57

3.3.3 Main results for stochastic model

The main results of the stochastic model for the considered UC, analysing the most provable scenario (Scenario 13), are presented in Figure 18 – Figure 22. Hence, Figure 18 shows the production and consumption results for this scenario. As can be observed, in this scenario, the stochastic model, like the deterministic model, manages the charging of the BESSs and EVs to take advantage of the available generator power. Hence, the peak charging of the BESS (34.00kW) occurs at 13h00, and for the EVs (49.35kW), at 16h00. In terms of energy production, the model manages the discharge of both the BESSs and EVs to alleviate system stress during periods when generators have low energy availability. Consequently, there is a high discharge from the BESSs at 3h00, reaching 12.98kW, and again at 19h00 with 14.86kW. Meanwhile, the EVs exhibit significant discharges at 10h00 with 7.2kW, at 19h00 with 12.54kW, and at 21h00 with 11kW. On the other hand, due to the inherent uncertainties of the stochastic model, it was not possible to avoid load reduction in this scenario, resulting in a peak reduction of 3.95kW at 22h00. Another point related to this model when compared to the deterministic model is that under uncertainty, the optimisation model opts to reduce the BESS charging/discharging power, since for this model, the BESS charging reduces by 43.6% and the BESS discharging power reduces by 52.0%. For this day of operation, the generators were managed to operate at their maximum capacity, producing a total of 487.00kWh of energy, with 0.00kWh exported to the grid. The BESSs discharged a total of 88.46kWh, while the EVs discharged 57.72kWh, with a total load energy reduction of 32.45kWh, and requiring 1,755.58kWh of grid export energy. In terms of consumption, the system's total load reached 1,927.95kWh, while the BESSs charged a total of 67.46kWh and the EVs 393.48 kWh.

Different from the deterministic and metaheuristic models, the stochastic model incorporates the possibility of providing both up and down reserves to the system within its intelligent community management, through the grid import power and the power of the BESSs. Thus, Figure 18 includes, into the production, the scheduling of these reserves in scenario 13. As can be observed, the grid import power is alleviated through the scheduling of down reserve power in this scenario, particularly between 11h00 – 16h00, with the maximum down reserve offered at 12h00, reaching 57.96kW. This results in a net grid import power of 22.03kW at that hour. This down reserve is made possible due to the charging management of the EVs, which reach a low charging level at 12h00, with a consumption of 12.19kW, and the complete reduction in consumption from the BESSs, which draw 0kW at that time, demonstrating that from system point of view this reserve decrease the grid import power. The total down reserve energy for this scenario, considering the grid import power, is 164.41kWh. On the other hand, when using the grid import power, no up reserve is offered because the transformer power capacity is at its maximum level, making impossible to increase the generation. Related to the BESSs power, no down neither up power was offered through this resource in Scenario 13.

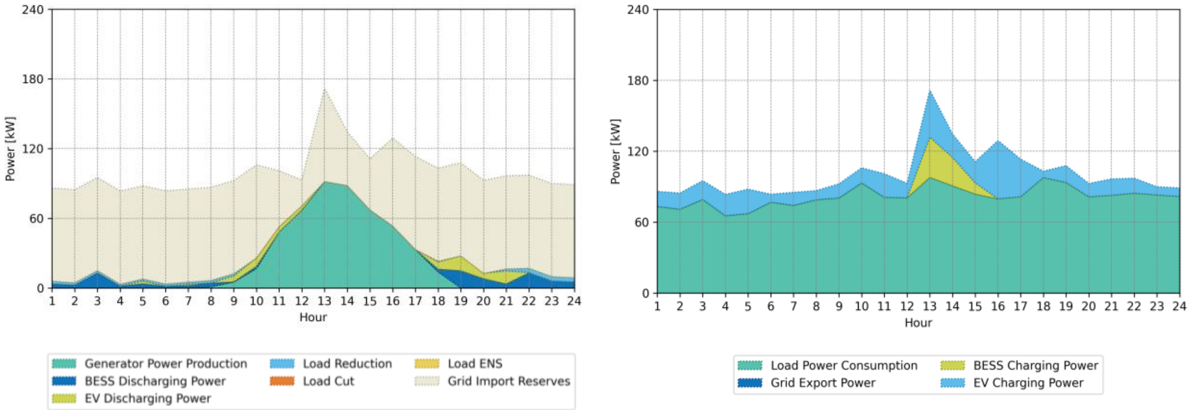

Figure 18 – Production (left side) and Consumption (right side) results for stochastic model, Method 1, Scenario 13

The down power reserves as well as the total down reserve energy offered in each scenario are illustrated in Figure 19. As shown, no grid import down reserves is offered in Scenarios 3, 4, and 5. The highest grid import down reserve energy is offered in Scenario 21, amounting to 448.76kWh, which corresponds to a 30.5% reduction in grid import generation in this scenario.

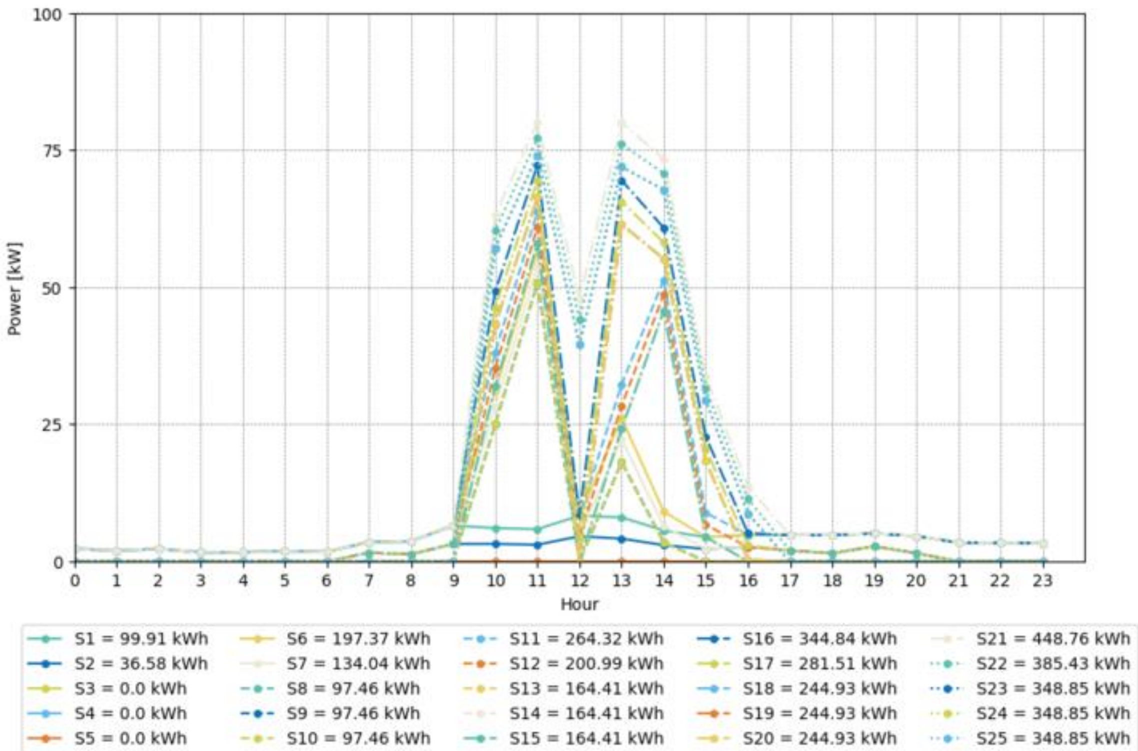

Figure 19 – Grid import down reserves for all scenarios, stochastic model, Method 1

Figure 20 presents the results for production (left side) and consumption (right side) of the stochastic model, under Method 2. It is important to highlight that for this method, since the input data comes from the real data module, the stochastic model only sees one scenario with a probability of 1.0. When comparing Method 1 with Method 2, it is evident that under the analysis of real data, where there was a 7.0% increase in generator availability on this day of operation, the algorithm takes advantage of this to increase the charging of both the BESS and EVs, as shown in Figure 20 (right side), increasing by 63.42% the BESS charging power, and by 7.73% the EVs charging power. Consequently, the EVs peak charging power occurs at 16h00 reaching 47.74kW, while the BESSs reach their peak charging power at 14h00 with 60.53kW.

Regarding production, it can be observed that due to the increased availability of generators, Method 2 exhibits more periods with reduced grid import power, particularly at 11h00, 12h00, and 14h00. The greatest reduction occurs at 12h00, with only 10.94kW being imported. During this time, the system's total load (82.25kW, considering both normal loads and EVs) is primarily supported by the generators, providing 63.44kW and with a small contribution from the EVs with 8.16kW. It is important to note that some vehicles are discharged while others are charged, always within their operational limits. On the other hand, like Method 1, in Method 2, the BESSs and EVs are also managed by the algorithm to help meet the system's load, particularly during periods with no generators power availability. Between 1h00 – 4h00, the BESSs are primarily utilized to support the grid, even reaching their peak discharge power of 57.84kW at 3h00. The EVs, in turn, are used between 19h00 – 21h00 to complement the grid, notably after the BESSs have been heavily utilized. The EVs reach their peak discharge power of 22kW at 22h00, supporting the grid during hours when community users are expected to have returned to the EVSEs. Regarding consumption, the algorithm leverages the increased availability of generators to enhance the charging of BESSs and EVs during peak production hours (11h00 – 17h00), thereby improving the community's utilization of sustainable resources. Finally, on this operational day, total grid import energy amounted to 1823.40kWh, while total BESS discharging energy reached 194.69kWh, the total EV discharging energy was 89.56kWh, and generator energy production was 496.25kWh. As a result, under this method incorporating real-time data, generator power production exhibited a 7% increase compared to method 1. Furthermore, as with method 1, method 2 showed no load reduction, load cut, or load ENS. In terms of consumption, this method, resulted in total EV consumption of 426.44kWh, with a total BESS charging energy of 184.42kWh. The overall load consumption reached 1992.50kWh. Moreover, when considering real data, this method does not provide up or down reserves for either grid import power or BESSs.

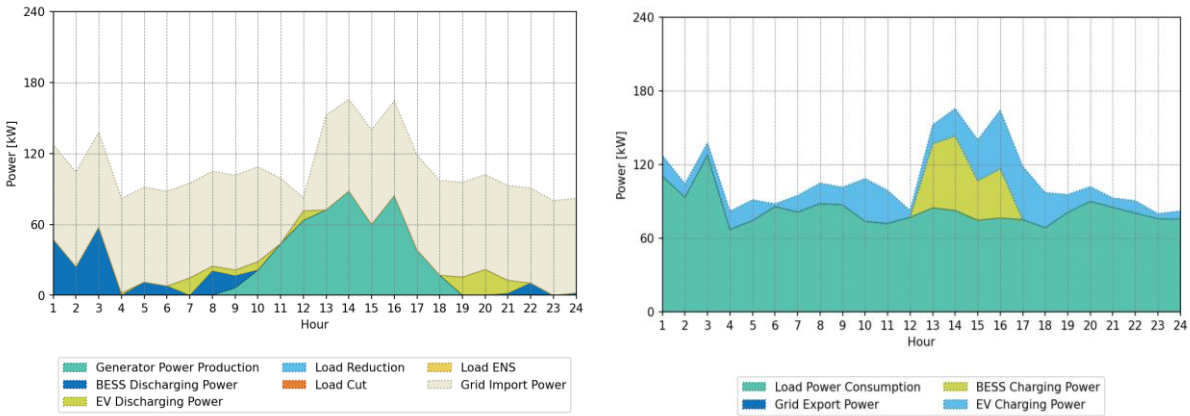

Figure 20 – Production (left side) and Consumption (right side) results for stochastic model, Method 2

Figure 21 illustrates production (left side) and consumption (right side) results for the stochastic model, Method 3. As can be observed, for this method, the stochastic model, due to the high uncertainty, presents an increase related to the load reduction power, with a peak of 51.49kW at 3h00. Despite the high uncertainty of this model and method, the optimisation model takes advantage of the maximum availability of generators to charge both BESSs and EVs. Hence, the peak charging of the BESS (36.12kW) occurs at 13h00, and for the EVs (49.35kW), at 16h00. In terms of energy production, the model manages the discharge of both the BESSs and EVs to alleviate system stress during periods when generators have low energy availability. Consequently, there is a high discharge from the BESS at 3h00, reaching 11.56kW, and again at 22h00 with 10.77kW. Meanwhile, the EVs exhibit significant discharges at 10h00 with 7.2kW, at 19h00 and at 18h00 with 17.09kW. For this day of operation, the generators were managed to operate at their maximum capacity, producing a total of 496.37kWh of energy, with 0.00kWh exported to the grid. The BESSs discharged a total of 88.63kWh, while the EVs discharged 57.72kWh, with a total load energy reduction of 221.93kWh. In terms of consumption, the system's total load reached 1,770.57kWh, while the BESSs charged a total of 106.47kWh and the EVs 393.48 kWh. Figure 21 includes, into the production, the scheduling of the down reserve power in Scenario 13. As can be observed, the grid import power is alleviated through the scheduling of down reserve power in this scenario, particularly between 6h00 – 19h00, with the maximum down reserve offered at 12h00, reaching 53.12kW. This results in a net grid import power of 26.87kW at that hour. This down reserve is made possible due to the charging management of the EVs, which reach a low charging level at 12h00, with a consumption of 12.19kW, and a BESSs charging power of 4.52kW at that time, demonstrating that from system point of view this reserve decrease the grid import power. The total down reserve energy for this scenario, considering the grid import power, was 251.44kWh. On the other hand, using the grid import power, no up reserve is offered, this because the power capacity of the transformer is used at its maximum level makes impossible to increase the generation. Related to the BESSs power, no down neither up power was offered through this resource in Scenario 13.

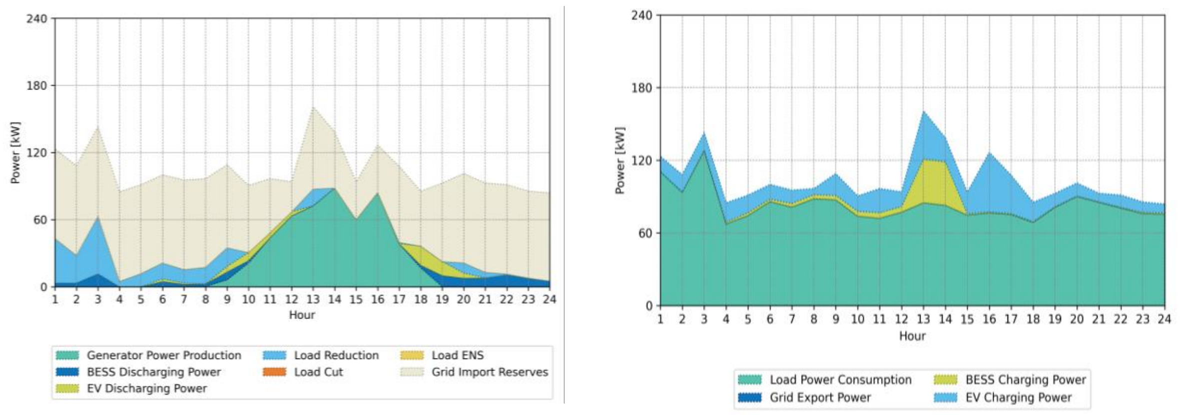

Figure 21 – Production (left side) and Consumption (right side) results for stochastic model, Method 3, Scenario 13

Due to the high uncertainty of the stochastic model for Method 3, the community's power consumption was adjusted through load reduction and load cut. As a result, the system's net consumption load is presented in Figure 22. Thus, it is possible to observe how the load power consumption curve is adjusted aligning with the peaks of load reduction and load cut.

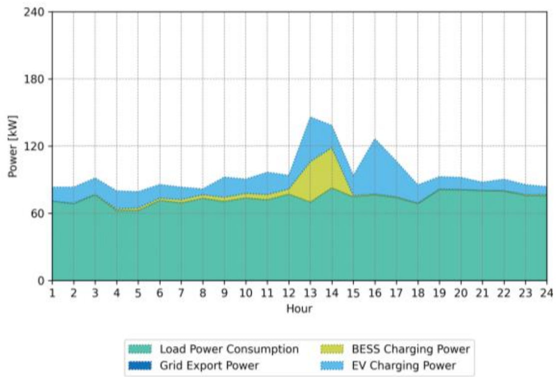

Figure 22 – Net consumption results for stochastic model, Method 3, scenario 13

Table 4 provides a summary of energy production and consumption for each method in the UC analysis based on the stochastic model, specifically for Scenario 13. When incorporating both forecast data and a mix of forecast and real data to predict future actions, the optimization model fails to efficiently manage the energy community, resulting in an inability to prevent load reduction. A noteworthy observation is that in Method 3, when uncertainty is high, the model allocates more down reserves compared to the other methods.

Table 4: Summary of the energy production and consumption (kWh) for the three methods of the stochastic model, Scenario 13

Method	Energy Imported	Final Load energy consumption	Community Load Energy consumption	Energy reduction	Energy cut	Energy ENS	Generators energy	BESS and EVs Energy discharging	Energy exported
Method 1	1,755.59	2,256.53	1,795.58	32.45	0.00	0.00	487.12	146.18	0.00
Method 2	1,823.41	2,603.37	1,992.50	0.00	0.00	0.00	496.37	283.59	0.00
Method 3	1,627.80	2,270.53	1,770.57	221.92	0.00	0.00	496.37	146.35	0.00

4 Conclusions

This deliverable presents a methodology for the optimal management of energy communities. The core of the methodology is an adaptable computational tool that operates based on three distinct models: deterministic, metaheuristic, and stochastic. Each model utilizes data from different sources: Method 1 uses input data from a forecasting module, Method 2 relies on real data, and Method 3 combines forecasting information with real data, comparing them to predict future actions. The stochastic model considers five scenarios related to consumption and five scenarios related to production. A key innovation of the stochastic model, compared to the deterministic and metaheuristic models, is its ability to offer up and down power reserves using both the grid and battery energy storage systems (BESSs). Overall, a key conclusion is that both the deterministic and stochastic models demonstrate excellent management of resources within the energy community. In the case of the stochastic model, this includes scheduling reserves based on imported grid power. In contrast, the metaheuristic models exhibit poor performance, using the available resources inefficiently.

In a deeper analysis of the results, it is possible to conclude that:

- The deterministic model implements an optimal energy community management when using both forecast and real input data, successfully allocating the charging of BESSs and EVs during periods of high generator availability, while managing their discharging during times of limited generator power. This is achieved without exporting power to the grid nor reducing and curtailing load consumption of the community. However, when combining forecast and real data to predict future actions, due to the uncertainties handled in Method 3, the deterministic model is forced to reduce load energy to meet an increased demand, particularly from EVs and BESSs, resulting in a 5% and 6% increase in demand compared to Cases 1 and 2, respectively.
- The metaheuristic model has poor performance by using the Dandelion Optimizer in the three methods analysed. The algorithm executed a suboptimal EV and BESS charging management since the generators maximum availability production power is not used to serve their power consumption leading to have export energy to the grid in the three methods. On the other hand, the algorithm is incapable of avoiding load curtailed and reduction, requiring 2.0% more power than necessary for Method 1, 2.6% for Method 2, and 26.0% for Method 3. Hence, this confirm that metaheuristic models are not recommended to be used for energy community management.
- The stochastic model, like the deterministic model, yields optimal results when it comes to the management of BESS and EV power, prioritizing the utilization of periods with higher generator availability to increase their charging. However, when compared to the deterministic model, and due to the uncertainties addressed, the stochastic model prefers to reduce the total consumption of BESS by up to 52%. Nevertheless, it maintains the energy demanded by EVs at the same level as the deterministic model, confirming that even with uncertainties, the comfort of e-mobility users is preserved.
- The provision of down reserves in the stochastic model indicates that the management of EVs and BESS is designed to alleviate demand from the system's perspective. When considering forecast data, the model prioritizes reducing grid demand by offering down reserves.

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