Optimal Management of Energy Communities considering Electric Mobility

Larissa Montefusco[1], Tomás Glória[2], Cindy P. Guzman[1], Hugo Morais[1*]

[1]INESC ID, Department of Electrical and Computer Engineering, Instituto Superior Técnico—IST, Universidade de Lisboa, Lisboa, Portugal,
hugo.morais@tecnico.ulisboa.pt

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Abstract

Energy Communities (ECs) are emerging empowering consumers and creating new business opportunities for end consumers and for companies that will take the management of these communities. Considering the characteristics of the communities' storage systems is key to balancing production and consumption in different periods of time. With an optimal management of the storage, it is also possible to take advantage of the volatile prices of electricity markets charging when the prices are low (or even negative) and discharge when the prices are high. This paper explores an optimal management approach that integrates day-ahead scheduling with real-time control to enhance the efficiency and effectiveness of ECs operations. Considering day-ahead scheduling, two optimal functions will be presented namely the cost minimization and the self-consumption maximization. Concerning real-time control, the main aim is to follow the scheduling or, in other words, minimize the deviations. In the present method the deviations are measured mainly in the State-of-Charge of the storage systems. The use case (UC) involves an energy community comprising 20 participants, yielding very interesting results when compared to traditional control methods that aim to follow the scheduled production, or the energy imported from the main grid.

Nomenclature

B	Set of batteries
EV	Set of electric vehicles
G	Set of generators
L	Set of loads
$C_{t,b}^{B+}$	Cost associated with battery charge
$C_{t,b}^{B-}$	Cost associated with battery discharge
$C_{t,ev}^{EV+}$	Cost associated with electric vehicle charge
$C_{t,ev}^{EV-}$	Cost associated with electric vehicle discharge
$C_{t,g}^{G+}$	Cost associated with power imported
$C_{t,g}^{G-}$	Cost associated with power exported
$C_{t,l}^{c}$	Cost associated with energy curtailed
$C_{t,l}^{ENS}$	Cost associated with energy not supplied
$C_{t,l}^{r}$	Cost associated with energy reduced
C_{t}^{buy}	Cost associated with system's imported power
C_{t}^{sell}	Cost associated with system's exported power
$L_{t,l}^{c}$	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
$P_{t,b}^{B+}$	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
$P_{t,ev,w}^{EV+}$	Power charged by the electric vehicles
$P_{t,ev,w}^{EV-}$	Power discharged by the electric vehicles
$P_{t,g}^{G+}$	Power imported by generators
$P_{t,g}^{G-}$	Power exported by generators

1 Introduction

Energy Communities (ECs) present a promising model for decentralizing energy systems by enabling collective management of energy use, which may include renewable energy sources (RESs). The integration of Vehicle-to-Everything (V2X) technologies allows electric vehicles (EVs) to function as both energy consumers and mobile energy storage units, taking on versatile roles within ECs.

Initial studies have focused on understanding the social arrangements behind ECs, aiming to identify their strengths and limitations in fostering collaboration, engagement, and efficient energy use [1], [2], [3]. At the same time, as these technologies evolve, the development of algorithms to optimize energy consumption and generation has become increasingly important [4]. Various methods have been explored, including the use of smart charging and discharging strategies for self-consumption energy management, as proposed in [5]. For instance, different types of models, such as metaheuristic [6], [7] and stochastic [8], [9] approaches, have been employed in several studies. Nevertheless, deterministic models deliver better results due to their ability to minimize uncertainty compared to metaheuristic and stochastic models.

As part of the European project Electric Vehicle Management for Carbon Neutrality in Europe (EV4EU), this paper aims to propose an optimized approach to managing energy communities while prioritizing users' needs. The proposed methodology has been validated in a realistic scenario, utilizing data inputs from an EC that integrates the main grid, photovoltaic (PV) systems, battery energy storage systems (BESSs), electric vehicles (EVs), electric vehicle supply equipment (EVSEs), and typical load profiles. These inputs were sourced from a database containing real-world records from several residential households on a Portuguese island [10], along with energy pricing data from the Iberian market [11].

2 Deterministic Optimization Problem

The deterministic optimization problem is implemented by Python Energy Communities (PyECOM), a user-friendly Python-based algorithm developed to facilitate the analysis, simulation, and optimization of energy communities. PyECOM includes a robust optimization model that considers energy production, consumption, storage, and distribution [4].

To enhance the functionality of PyECOM's deterministic optimization model, three distinct methods were developed to modify the input data for load and production across different scenarios. Method 1 incorporates data from a forecasting module, which is trained using historical data from Method 2. Method 2 utilizes real-time data, as referenced in [10], while Method 3 combines both forecasting and real-time data to provide a more comprehensive input for the optimization model.

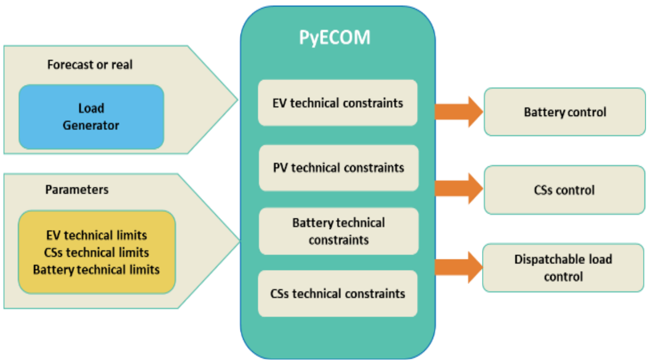

Figure 1 – Input data process in the PyECOM tool for Method 1 (forecasting data) and Method 2 (real data).

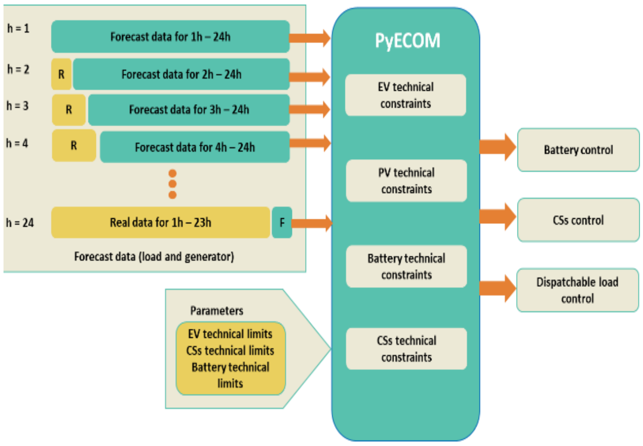

Figure 2 – Input data process in the PyECOM tool for Method 3 (mixed data – forecasting and real).

The PyECOM deterministic model objective function (OF) focuses on minimizing costs and maximizing self-consumption; in other words, it aims to utilize the community's resources as efficiently as possible. As expressed in Equation (1), the OF integrates five critical components that reflect the energy dynamics within the system. These components are detailed in subsequent equations: generators (2), loads (3), BESS (4), EVs (5), and the broader system operations (6).

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

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

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

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

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

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

Each equation relates to the energy production or consumption of individual components and the corresponding energy prices, with Δ_t denoting the time interval. 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.

3 Case of Study and Results

3.1 Case of Study

To test the proposed optimization approach, a case study was chosen involving an EC with 20 participants, including 4 small commercial buildings and 16 residential households. Additionally, the community includes twenty BESS, one for each location, sixteen EVSE units, thirty-two EVs, and twenty generators (considered as PV units, one per location**).** Furthermore, the technical constraints of the distribution network are considered, including a local transformer with a nominal capacity of 100 kW, subject to an 80% usage limit.

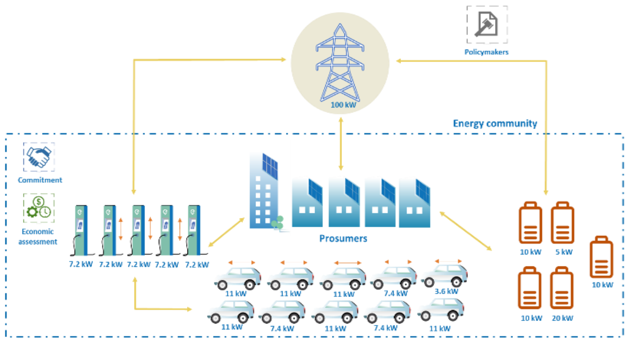

Figure 3 – Energy Community scenario considering stationary storage and electric vehicles

The following outlines the efficiency assumptions and configurations applied to each component:

Category	Quantity	Charging efficiency	Discharging efficiency
BESS	20	0.95	0.96
EVSE with V2X	10	0.95	0.95
EVSE without V2X	6	0.95	1.00
EVs with V2X	18	0.98	0.98
EVs without V2X	14	0.98	1.00

About the input data, the forecasted generator peaks for the four commercial buildings are 7.5kW, 11.75kW, 16.09kW, and 20.6kW, while residential houses are expected to remain below 3.6kW. However, real data reveals higher peaks for the commercial buildings at 9.3kW, 14.4kW, 19.8kW, and 25.4kW, whereas residential houses show lower peaks, staying under 2.8kW. Forecasted load consumption for the four commercial buildings is 31.23kW, 24.3kW, 17.7kW, and 11.41kW, while residential houses remain below 4.7kW. Real data shows higher peaks for the buildings at 40.29kW, 31.33kW, 22.88kW, and 14.73kW, and for residential houses at under 5.8kW. Plots of the input data for generators used in Method 1 (Forecasting Data) and Method 2 (Real Data) are illustrated in Figure 4 and Figure 5, respectively.

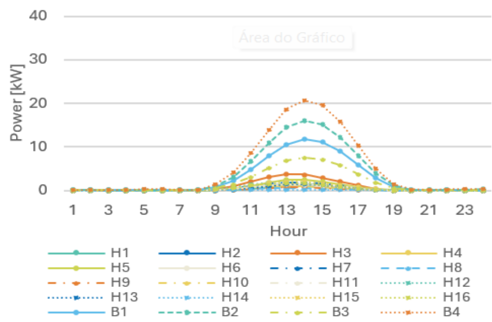

Figure 4 – Generators profiles for Method 1 – Forecasting Data

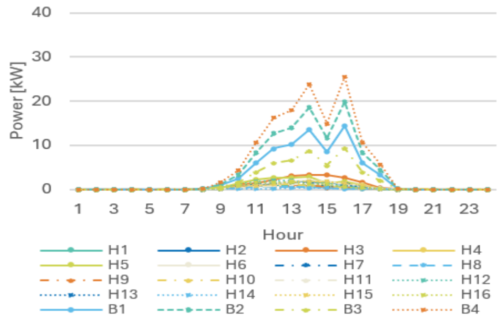

Figure 5 – Generators profiles for Method 2 – Real Data

The input data for load consumption used in Method 1 (Forecasting Data) and Method 2 (Real Data) are depicted in Figure 6 and Figure 7 respectively.

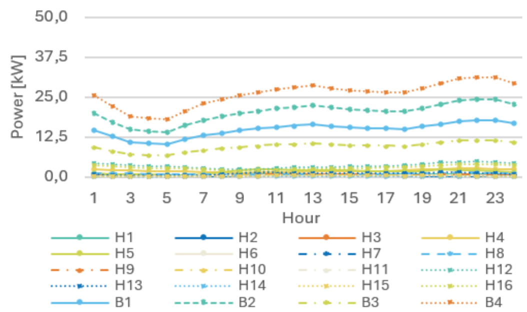

Figure 6 – Load consumption for Method 1 – Forecasting Data

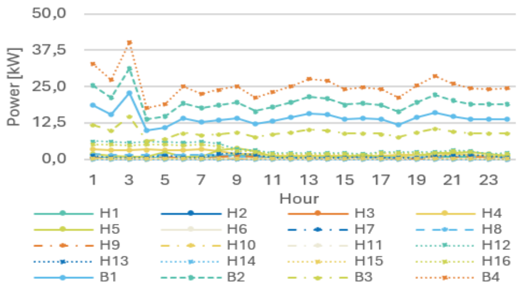

Figure 7 – Load consumption for Method 2 – Real Data

3.2 Results

The results of the EC management using Method 1 inputs show that grid import power peaked at 80 kW, coinciding with increased generator production at 12:00. EV discharges occurred during peak consumption hours (19:00 – 23:00), while BESS discharged from 01:00 to 03:00. During high solar production (13:00 – 15:00), EVs and BESS were charged, reaching peaks of 50.28 kW and 49.35 kW, respectively. There was no load reduction or energy export to the grid. Total load consumption was 2040.80 kWh, with grid import energy of 1896.77 kWh, BESS discharging energy of 156.64 kWh, and EV discharging energy of 49.68 kWh.

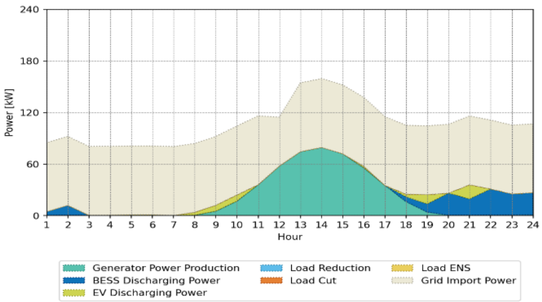

Figure 8 – Production for the model using Method 1.

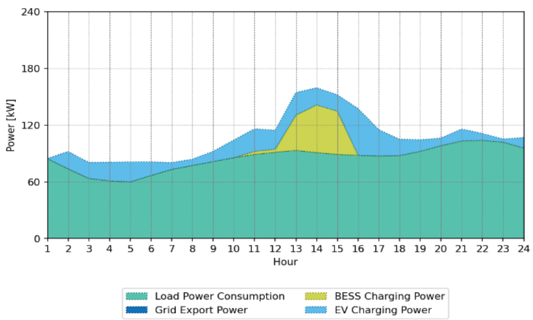

Figure 9 – Consumption for the model using Method 1.

Method 2 capitalizes on a 7% increase in generator availability, leading to higher charging of BESS (54.69 kW) and EVs (46.07 kW) compared to Method 1. This results in reduced grid imports, particularly at 12:00 (17.42 kW). BESS discharges at night (peaking at 59.42 kW at 3:00), while EVs discharge from 6:00 to 12:00. The algorithm optimizes charging during peak solar production (11:00 – 17:00). By the end of the day, grid imports totaled 1823.40 kWh, BESS discharged 194.69 kWh, EVs 89.56 kWh, and generators produced 496.25 kWh, with no load reduction or energy export.

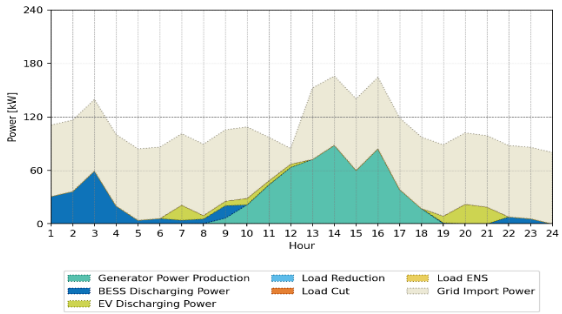

Figure 10 – Production for the model using Method 2.

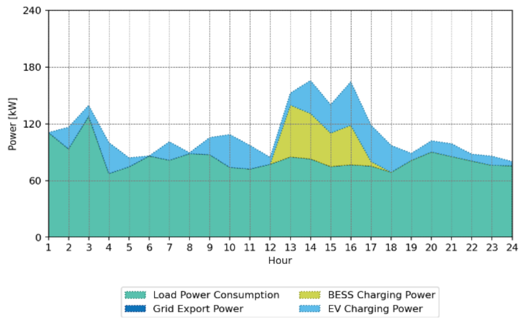

Figure 11 – Consumption for the model using Method 2.

For method 3, 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. EVs reached their peak charging power at 16:00 (49.83 kW), and BESSs peaked at 14:00 (68.08 kW), utilizing generator power. At 16:00, grid import power was minimized due to generator availability and a small contribution from EVs (1.23 kW). BESSs supported the grid during high demand periods (1:00–3:00 and 20:00–24:00), with a peak discharge of 33.75 kW at 22:00. EVs contributed from 18:00 to 22:00, with a peak discharge of 15.41 kW at 21:00.

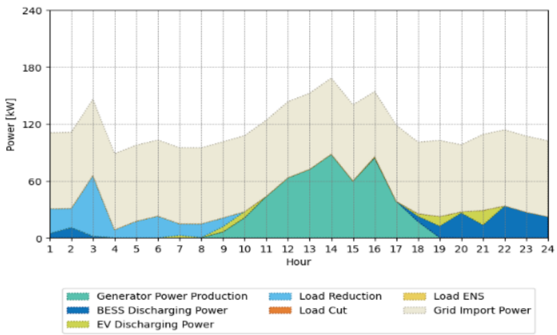

Figure 12 – Production for the model using Method 3.

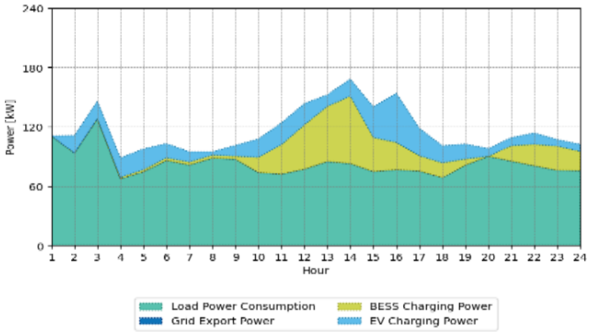

Figure 13 – Consumption for the model using Method 3.

4 Conclusion

Based on the analysis, the deterministic model effectively optimizes energy community management by utilizing both forecasted and real input data. It successfully allocates energy for BESS and EV charging during periods of high generator availability while managing discharging during times of limited power. This is achieved without the need to export energy to the grid or reduce the community's load consumption. However, when combining forecast and real data, the model faces uncertainties that lead to a 5% and 6% increase in demand, particularly from EVs and BESSs, compared to scenarios using only forecast or real data. This highlights the challenge of handling uncertainties in future predictions and their impact on overall demand management.

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