Sizing Distributed Energy Resources for Energy Communities

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***Abstract*—Renewable energy resources are crucial for addressing global economic and environmental challenges. Energy communities, which unite consumers to pursue shared energy goals, present a promising solution for reducing energy costs and enhancing sustainability. This study analyzes the optimal sizing and operation of energy community resources, formulating the problem as mixed-integer linear programming (MILP) models. Two tools are employed: one for daily operation, calculating energy setpoints for community assets such as battery energy storage systems (BESS) and electric vehicles (EVs), and another for sizing photovoltaic (PV) panels and BESS capacities to minimize costs while optimizing local energy trades. Due to the high computational demands of MILP, three optimization methods are compared: deterministic, hybrid particle swarm optimization (PSO), and evolutionary PSO (EPSO). The hybrid PSO method handles binary and continuous variables efficiently, while EPSO introduces diversity to improve solution quality in complex scenarios. These metaheuristic approaches address the trade-off between solution accuracy and computational effort, providing reliable tools for decision-makers in energy communities.**

***Index Terms*-- Distributed energy resources, Energy community, Metaheuristics, Optimization, Sizing and planning.**

I. INTRODUCTION

A. Background and motivation

Renewable energy systems (RES) play a crucial role in addressing global economic and environmental challenges, offering sustainable alternatives to conventional energy sources. In this context, energy communities (ECs) have emerged as a promising approach to integrate RES efficiently, by facilitating energy sharing among members, reducing the energy exchanged between each member and their energy retailer and/or aggregator. This energy sharing leads to significant economic savings for both the members and the community, depending on the chosen business model and the existing regulatory framework, therefore, optimal resource allocation and asset sizing are essential [1]. This paper focuses on the operation and sizing of energy assets within renewable energy communities (RECs), framed as a MILP problem. The operation tool calculates the daily setpoints for energy use and flexible assets of community members, such as loads, BESS, EVs, and electric water heaters (EWH). The sizing tool determines the optimal capacities of photovoltaic panels and BESS to minimize community energy costs, considering their optimal operation and local energy trades among members. Given the computational intensity of MILP, metaheuristic approaches are investigated to enhance computational performance. This paper compares MILP, PSO and EPSO approaches. By analyzing these methods, this work offers tools for decision-makers in RECs, highlighting the trade-offs between computational effort and solution accuracy. This contributes to optimizing resource planning and operational efficiency while maximizing the economic and environmental benefits for the community.

B. Literature review

The optimal sizing and operation of REC assets has been extensively addressed in the literature. The MILP method is selected due to its ability to handle both continuous and discrete variables, allowing for a precise representation of real-world problems that include binary choices (e.g., switching on/off devices) and discrete resource allocations. However, despite its advantages in accuracy, MILP poses significant computational challenges, especially as problem size and complexity grow, leading to high computational demands and longer solution times. Several examples of REC sizing and operation via MILP can be found in the literature. For example, [2] has proposed an optimal sizing and operation planning method using mixed-integer linear programming for RECs costs minimization, showing that all community members achieved both economic advantages (a 15% reduction in costs) and environmental benefits (a 34% decrease in CO2 emissions), irrespective of the tariff model chosen. Similar approaches are found in [3] and [4]. In [5] - [6], a stochastic approach was also added to the MILP-based optimization framework to address load and PV uncertainty. As previously mentioned, MILP approaches, while promising, are computationally more demanding than metaheuristic methods, particularly as problem size and complexity increase, especially with non-linear constraints, as noted in [7]. This has led to a growing research interest in the application of metaheuristic techniques for ECs.

From [8], it is inferred that PSO performs better and is more robust than other heuristic algorithms, as it efficiently handles the non-linear and multi-dimensional nature of EC optimization problems. For instance, in [9] and [10], the optimal sizing of production and storage units within renewable energy communities was achieved using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm with multiple swarms. This approach aimed at fostering a greater diversity of solutions while maintaining a good set of non-dominant solutions that define the Pareto frontier. However, while PSO provides promising results, further improvements have been made with the development of EPSO. EPSO builds upon PSO's strengths by incorporating mechanisms such as self-adaptation and evolutionary strategies, improving convergence and solution accuracy. These improvements are demonstrated in [11], where EPSO outperformed PSO in terms of computational efficiency and solution quality for EC optimization tasks.

C. Main contributions

This paper presents a methodology derived from the approach developed within the ENPOWER (EU project) [12] [13], based on the electric assets module of INESC TEC [14]. The main contribution of this work lies in advancing the application of PSO for the sizing and operation of RECs, while also exploring the potential of EPSO for these purposes, which remains unexplored in the existing literature. By comparing EPSO with traditional MILP methods and PSO as a representative metaheuristic algorithm, valuable insights into the potential advantages of EPSO will be provided, particularly in terms of computational efficiency and solution quality handling complex optimization problems.

D. Paper structure

The rest of this paper is structured as follows. In Section II the mathematical framework and computational implementation are introduced. Section III regards the metaheuristic algorithms introduction. Section IV characterizes the case study and presents the numerical results. Finally, the paper is concluded in Section V.

II. COMPUTATIONAL IMPLEMENTATION

SITEC is the electric assets sizing module related to ENPOWER (EU project), which focuses on the sizing of each individual and shared asset, such as PV panels and BESS for the REC. It also accounts for energy sharing among members (or within the community) and the calculation of the energy bill for the REC and its members [13].

A. Mathematical model

The proposed electric assets sizing module can be modeled as an optimization problem since it aims to minimize the total REC energy cost, including operation and investment costs. Thus, it is represented by a MILP model, and the problem consists of the minimization of a multimodal function with many local minima and a global optimum.

Assumptions

In this formulation, the following assumptions are made regarding the REC model. The REC consists of N prosumers, each with a defined consumption profile, and may include PV systems and individual batteries, including those initially installed. The consumption and production profiles, along with the technological characteristics of the assets, are assumed to be available. The opportunity costs for REC members are predefined and can vary according to their suppliers and aggregators. In scenarios where REC generation exceeds consumption, surplus energy may be sold to aggregators or retailers, whereas energy deficits are purchased from retailers. Grid constraints are not considered, and electricity demand is assumed to be inelastic, with flexibility provided by batteries and other flexible loads, altering the net consumption profile recorded by members' smart meters. Economies of scale in investment costs are excluded to avoid introducing non-linearity into the problem.

B. Mathematical Formulation

The objective function of SITEC leads to the minimization of the total REC energy cost, including operation and investment costs and it can be written as in equation (1).

$$min \sum_{n\epsilon N} \left(\begin{array}{c} \sum_{t\epsilon T} \left(\left(\begin{array}{c} E_{n,t}^{SUP} \cdot \hat{\lambda}_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \hat{\lambda}_{n,t}^{sell} \\ + E_{n,t}^{SLC} \cdot \hat{\lambda}_{t}^{grid} + \\ pen_{t}^{comf} \cdot a_1 \end{array} \right) \cdot \widehat{w}_{n,t}^{cluster} + \right) \\ (P_n^{cont} \cdot \hat{\lambda}_n^{cont} + P_n^{GN} \cdot \hat{\lambda}_n^{G,ic} + E_n^{BN} \cdot \hat{\lambda}_n^{B,ic}) \cdot \widehat{D} \end{array} \right) \quad (1)$$

The constraints of the optimization model are defined in equations (2) – (45), which apply to each time period $\forall\ t \in T$ and each meter $n \in N$, unless stated otherwise [13]. The net consumption at meter *n*, at time *t* and its constraints are illustrated in the equations (2) – (8).

$$\mathrm{E}_{\mathrm{n,t}}^{\mathrm{CMET}} = \widehat{\mathrm{E}}_{\mathrm{n,t}}^{\mathrm{C}} - \mathrm{E}_{\mathrm{n,t}}^{\mathrm{G}} + \mathrm{E}_{\mathrm{n,t}}^{\mathrm{B,C}} - \mathrm{E}_{\mathrm{n,t}}^{\mathrm{B,D}} + \sum_{\mathrm{ev} \in \mathrm{EV}} \left(\mathrm{P}_{\mathrm{n,ev,t}}^{\mathrm{EV,C}} - \mathrm{P}_{\mathrm{n,ev,t}}^{\mathrm{EV,D}}\right) \quad (2)$$

$$E_{n,t}^{CMET} = E_{n,t}^{SUP} - E_{n,t}^{SUR} + E_{n,t}^{PUR} - E_{n,t}^{SALE} \quad (3)$$

$$E_{n,t}^{CMET+} \geq E_{n,t}^{CMET} \quad (4)$$

$$\sum_n E_{n,t}^{CMET} \geq -\widehat{M} \cdot \delta_t^{rec\_bal} \quad (5)$$

$$\sum_n E_{n,t}^{CMET} \leq \widehat{M} \cdot \left(1 - \delta_t^{rec\_bal}\right) + \widehat{m} \quad (6)$$

$$E_{n,t}^{CMET} \geq -\widehat{M} \cdot \delta_{n,t}^{meter\_bal} \quad (7)$$

$$E_{n,t}^{CMET} \leq \widehat{M} \cdot \left(1 - \delta_{n,t}^{meter\_bal}\right) + \widehat{m} \quad (8)$$

Equations (9) – (10) define the contracted power per meter and limit it to the maximum CPE power limit and equations (11) – (13) establish the installed RES capacity and its limit and the total RES generation.

$$-P_n^{CONT} \le E_{n,t}^{CMET}/\Delta t \le P_n^{CONT} \quad (9)$$
$$P_n^{CONT} \le \hat{P}_n^{CPE,max} \quad (10)$$
$$P_n^{GN} = P_n^{GN,total} - \hat{P}_n^{GN,init} \quad (11)$$
$$E_{n,t}^{G} = \hat{f}_{n,t}^{G} \cdot P_n^{GN,total} \cdot \Delta t \quad (12)$$
$$\hat{P}_n^{GN,min} \le P_n^{GN} \le \hat{P}_n^{GN,max} \quad (13)$$

The constraints and operational characteristics of battery storage systems are shown in equations (14) – (20).

$$E_n^{BN} = E_n^{BN,total} - \hat{E}_n^{BN,init} \quad (14)$$
$$\hat{E}_n^{BN,min} \le E_n^{BN} \le \hat{E}_n^{BN,max} \quad (15)$$
$$E_{n,t}^{B,i}/\Delta t \le E_n^{BN,total} \cdot \hat{P}^{B,ref}/\hat{E}^{B,ref} \qquad i \in (C,D) \quad (16)$$
$$E_n^{B,init} = \widehat{SOC}_n^{B,min}/100 \cdot E_n^{BN,total} \quad (17)$$
$$E_{n,t}^{B} = \begin{cases} E_n^{B,init} + \left(E_{n,t}^{B,C} \cdot \hat{\eta}_n^{B,C} - E_{n,t}^{B,D}/\hat{\eta}_n^{B,D}\right) & t = 0 \\ E_{n,t-1}^{B} + \left(E_{n,t}^{B,C} \cdot \hat{\eta}_n^{B,C} - E_{n,t}^{B,D}/\hat{\eta}_n^{B,D}\right) & \forall\, t > 0 \end{cases} \quad (18)$$
$$\widehat{SOC}_n^{B,min} \cdot E_n^{BN,total} \le E_{n,t}^{B} \le \widehat{SOC}_n^{B,max} \cdot E_n^{BN,total} \quad (19)$$
$$E_{n,t}^{B} = E_n^{B,init} \qquad \forall\, t \in T^{24} \quad (20)$$

Equations (21) – (31) characterize the energy balance and allocation rules for the system.

$$\begin{cases} E_{n,t}^{SUP} \le \widehat{M} \cdot \left(\delta_{n,t}^{SUP}\right) + \widehat{m} \\ E_{n,t}^{SUR} \le \widehat{M} \cdot \left(1 - \delta_{n,t}^{SUP}\right) + \widehat{m} \end{cases} \quad (21)$$
$$E_{n,t}^{ALC+} \ge E_{n,t}^{PUR} - E_{n,t}^{SALE} \quad (22)$$
$$E_{n,t}^{SLC} \ge E_{n,t}^{CMET+} - \widehat{M} \cdot (1 - \delta_{n,t}^{SLC}) \quad (23)$$
$$E_{n,t}^{SLC} \ge E_{n,t}^{ALC+} - \widehat{M} \cdot \delta_{n,t}^{SLC} \quad (24)$$
$$\textstyle\sum_n\left(E_{n,t}^{PUR}\right) - \sum_n\left(E_{n,t}^{SALE}\right) = 0 \quad (25)$$
$$E_{n,t}^{SALE} - E_{n,t}^{PUR} \le -E_{n,t}^{CMET} + \widehat{M} \cdot \delta_{n,t}^{coeff} \quad (26)$$
$$E_{n,t}^{SALE} - E_{n,t}^{PUR} \le \widehat{M} \cdot \left(1 - \delta_{n,t}^{coeff}\right) \quad (27)$$
$$E_{n,t}^{SALE} \ge -E_{n,t}^{CMET} - \widehat{M} \cdot (1 - \delta_{n,t}^{meter\_bal} + \delta_t^{rec\_bal}) \quad (28)$$
$$E_{n,t}^{SALE} \le -E_{n,t}^{CMET} + \widehat{M} \cdot (1 - \delta_{n,t}^{meter\_bal} + \delta_t^{rec\_bal}) \quad (29)$$
$$E_{n,t}^{PUR} \ge E_{n,t}^{CMET} - \widehat{M} \cdot (1 - \delta_t^{rec\_bal} + \delta_{n,t}^{meter\_bal}) \quad (30)$$
$$E_{n,t}^{PUR} \le E_{n,t}^{CMET} + \widehat{M} \cdot (1 - \delta_t^{rec\_bal} + \delta_{n,t}^{meter\_bal}) \quad (31)$$

The equations related to the energy storage behavior of the electric vehicle battery within the energy network are (32) – (36) and positive variables' constraints are imposed in (37).

$$E_{n,ev,t}^{EV,S} = E_{n,ev,t-1}^{EV,S} + \hat{\eta}_{n,ev}^{EV,C} \cdot P_{n,ev,t}^{EV,C} - P_{n,ev,t}^{EV,D}/\hat{\eta}_{n,ev}^{EV,D} - \hat{E}_{n,ev,t}^{Trip} \qquad \forall t \in T \setminus t = 1 \quad (32)$$
$$P_{n,ev,t}^{EV,D}/\hat{\eta}_{n,ev}^{EV,D} \le \hat{P}_{n,ev}^{EV,DLimit} \cdot \hat{X}_{n,ev,t}^{EV} \cdot \triangle t \quad \hat{X}_{n,t}^{EV} \in \{0,1\} \quad (33)$$
$$\hat{\eta}_{n,ev}^{EV,C} \cdot P_{n,ev,t}^{EV,C} \le \hat{P}_{n,ev}^{EV,CLimit} \cdot \hat{X}_{n,ev,t}^{EV} \cdot \triangle t \quad \hat{X}_{n,t}^{EV} \in \{0,1\} \quad (34)$$
$$E_{n,ev,t}^{EV,S} \le \hat{E}_{n,ev}^{EV,BatCapacity} \quad (35)$$
$$E_{n,ev,t}^{EV,S} \ge \hat{E}_{n,ev}^{EV,MinC} \quad (36)$$
$$\begin{aligned} &E_{n,t}^{G}, E_{n,t}^{B,C}, E_{n,t}^{B,D}, E_{n,ev,t}^{EV,S}, P_{n,ev,t}^{EV,C}, P_{n,ev,t}^{EV,D}, E_{n,t}^{SUP}, \\ &E_{n,t}^{SUR}, E_{n,t}^{PUR}, E_{n,t}^{SALE}, E_{n,t}^{SLC}, P_n^{CONT}, P_n^{GN}, P_n^{GN,total} \\ &E_n^{BN}, E_n^{BN,total}, E_{n,t}^{B}, E_n^{B,init}, E_{n,t}^{CMET,+}, E_{n,t}^{ALC+} \ge 0 \end{aligned} \quad (37)$$

Equations (38) – (45) describe the operation of the Electric Water Heater, considering energy storage, heating, losses and temperature control.

$$\begin{cases} W_t^{tot} = W^{init} & t = 0 \\ W_t^{tot} = W_{t-1}^{water} + W_{t-1}^{in} + W_{t-1}^{loss} & t > 0 \end{cases} \quad (38)$$
$$W_t^{in} = \widehat{EWH}^{power} \cdot \Delta t \cdot \delta_t^{in} \cdot \Delta t \quad (39)$$
$$W_t^{loss} = \widehat{EWH}^{ht} \cdot \widehat{EWH}^{area} \cdot \Delta t \cdot \left(T_t^{EWH} - \hat{T}^{amb}\right) \quad (40)$$
$$\begin{cases} T_t^{EWH} = \widehat{EWH}^{StartTemp} & t = 0 \\ T_t^{EWH} = (W_t^{tot} \cdot 3600)/(\widehat{EWH}^{cap} \cdot \hat{c}) & t > 0 \end{cases} \quad (41)$$
$$\begin{cases} W_t^{min} \le W_t^{tot} \le W_t^{max} \\ \widehat{EWH}^{min} \le T_t^{EWH} \le \widehat{EWH}^{max} \end{cases} \quad (42)$$
$$\Delta\hat{\delta}^{use} = \hat{\delta}_t^{use} - \hat{\delta}_{t-1}^{use} \quad (43)$$
$$\begin{cases} W_t^{tot} \ge \hat{T}^{set} \cdot \widehat{EWH}^{cap} \cdot \frac{\hat{c}\cdot\Delta t}{3600} - pen_t^{comf} & \hat{\delta}_t^{use} = 1 \\ W_{t-1}^{tot} \ge \hat{T}^{set} \cdot \widehat{EWH}^{cap} \cdot \frac{\hat{c}\cdot\Delta t}{3600} - pen_{t-1}^{comf} & \begin{cases} \Delta\hat{\delta}^{use} \ne 0 \\ \Delta\hat{\delta}^{use} = -\hat{\delta}_{t-1}^{use} \end{cases} \end{cases} \quad (44)$$
$$\begin{cases} T_t^{EWH} \ge \hat{T}^{set} - \widehat{M} \cdot (1 - \delta_t^{aux}) \\ T_t^{EWH} \le \hat{T}^{set} + \widehat{M} \cdot \delta_t^{aux} \\ W_t^{mix} \underset{\le}{\ge} m_{\delta^{use}}^{bSet} \cdot \hat{\delta}_t^{use} + m_{T^{EWH}}^{bSet} \cdot T_t^{EWH} + b^{bSet} \underset{+}{-} \widehat{M} \cdot \delta_t^{aux} \\ W_t^{mix} \underset{\le}{\ge} m_{\delta^{use}}^{aSet} \cdot \hat{\delta}_t^{use} + m_{T^{EWH}}^{aSet} \cdot T_t^{EWH} + \\ \qquad b^{aSet} \underset{+}{-} \widehat{M} \cdot (1 - \delta_t^{aux}) \\ W_t^{mix} = T_t^{EWH} \cdot \dfrac{\hat{c} \cdot \Delta t}{3600} \end{cases} \quad (45)$$

III. METAHEURISTIC ALGORITHMS

Metaheuristic algorithms are optimization techniques designed to solve complex problems that traditional methods (like gradient-based techniques) struggle to address efficiently due to non-linearity, non-differentiability, or high-dimensionality. They employ randomness and iterative search strategies to explore the solution space, offering near-optimal solutions within reasonable computational time.

A. Particle Swarm Optimization

PSO is an optimization technique inspired by natural biological behavior, in which the search for an optimal solution is analogous to a group's pursuit of a better position. The algorithm works with a swarm of particles, each defined from: a position (x_i^t), representing the current solution, a velocity (v_i^t), determining its direction and step size, a personal best position (p_i), that is the best solution the particle has found so far and a global best position (g), the best solution found by the entire swarm. The update of a particle's velocity at time $t+1$ is given by the equation (46), that balances the inertia, the cognitive and the social components. The parameters w_{ik} are weights fixed in the beginning of the process, the terms r_x are random numbers sampled from a uniform distribution in [0,1] and D(t) is a function decreasing with the progress of iterations, reducing progressively the importance of the inertia term [15].

$$v_i^{t+1} = \underbrace{D(t)\, w_{i0}\, v_i^t}_{\text{Inertia}} + \underbrace{r_1 w_{i1}\, (p_i - x_i^t)}_{\text{Cognitive}} + \underbrace{r_2\, w_{i2}(g - x_i^t)}_{\text{Social}} \quad (46)$$

Once the velocity is updated, the position of the particle is updated with the particle movement rule:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (47)$$

B. Evolutionary Particle Swarm Optimization

EPSO is an enhancement of the standard PSO that integrates evolutionary mechanisms such as mutation, recombination (via particle movement rule) and selection to improve the algorithm's performance. The mutation is modelled as:

Weights mutation: $w_{ik}^* = w_{ik} + \tau N(0,1)$ (48)

Global best mutation: $g^* = g + \tau' N(0,1)$ (49)

Where N(0,1) is the standard Gaussian distribution and τ, τ' are fixed learning parameters, obtained by parameter tuning. The evolved parameters are incorporated into the velocity update as in equation (50), where P is the communication factor, set as an external parameter via parameter tuning, to control the passage of information within the swarm [15].

$$v_i^{t+1} = w_{i0}^*\, v_i^t + w_{i1}^*\, (p_i - x_i^t) + w_{i2}^*(g^* - x_i^t)\, P \quad (50)$$

IV. CASE STUDY

A. Case characterization

This case study evaluates the performance of the proposed optimization models in a REC comprising four prosumers connected through the public LV distribution grid. Each prosumer has the capacity to integrate behind-the-meter PV panels and battery energy storage systems and is equipped with two electric vehicles, and one electric water heater. The load and production profiles used in this study were obtained from real energy data collected and analyzed for the BeFlexible project [16]. The sizing process would require a full-year analysis to incorporate seasonal variations and ensure long-term accuracy. However, due to computational constraints, this study considers a single representative day for each season, obtained by clustering techniques, to balance computational efficiency with meaningful insights into system performance.

Data and parameters

After the experimentation procedure and parameters refinement, the PSO and EPSO attributes found to be the best for this problem are the ones selected for these tests, defined as follows: Number of particles = 1000; Maximum number of iterations = 5000; Inertia = 0.3; Cognitive value = 3; Social value = 2; Mutation rate = 0.3; Communication probability = 0.7; Alpha (α) = 6000; Beta (β) = 2.

The main data of the case study are summarized in Tables I–III. Each meter is assumed to have no pre-installed PV or BESS and the potential PV production is evaluated with a reference PV power of 1 kW.

TABLE I. CONSUMERS' CHARACTERISTICS

Meter ID	Annual Load [kWh]	Annual potential PV production [kWh]	Purchasing price [€/kWh]
M1	3883	563	0.16
M2	3278	867	0.18
M3	5079	563	0.14
M4	7237	867	0.17

TABLE II. EVs TECHNICAL AND USAGE DATA PER METER

Meter ID	M1		M2	
EV ID	**EV1**	**EV2**	**EV1**	**EV2**
Capacity [kW]	44	113	40.9	126
Charge/Discharge [kW]	55	48.8	74	47.8
Efficiency	0.97	0.95	0.86	0.92
Daily trip [km]	45	26	40	20
Consumption [kWh/km]	0.15	0.17	0.14	0.22
Trip consumption [kWh]	6.80	4.37	5.44	4.48
Meter ID	**M3**		**M4**	
EV ID	**EV1**	**EV2**	**EV1**	**EV2**
Capacity [kW]	43.5	205	42.9	109
Charge/Discharge [kW]	69.3	60.3	74	60.6
Efficiency	0.95	0.94	0.9	0.92
Daily trip [km]	44	16	24	18
Consumption [kWh/km]	0.13	0.14	0.14	0.22
Trip consumption [kWh]	5.81	2.19	3.36	4.01

TABLE III. EWH USAGE DATA PER METER

Meter ID	Timeslot	Duration [min]	Meter ID	Timeslot	Duration [min]
M1	08:00	10	M2	21:00	30
	08:15	10	M3	07:00	30
	12:00	5		20:00	20
	20:00	5		21:00	30
	22:00	20	M4	08:00	15
M2	07:00	30		13:00	15
	12:00	10		19:00	20
	20:00	10		22:00	30

The EWH unit is characterized by the capacity of 100 liters, the maximum power of 1.8 kW, the maximum internal temperature of 80 °C, the user comfort temperature of 40 °C and the heat exchange area of 1.3 m².

B. Results

Table IV presents the value of the objective function for each season regarding the three selected optimization approaches. The MILP approach is used as a reference due to its deterministic nature, achieving the lowest energy costs across all seasons. In comparison, the EPSO showed small deviations, around 2%, and PSO presented higher deviations, around 18%. Based on the simulations that were conducted, the algorithms achieved convergence after 233 iterations for EPSO and 1000 iterations for PSO. The corresponding execution times were around 120.07 seconds for MILP, 250.96 seconds for EPSO, and 491.65 seconds for PSO.

TABLE IV. VALUES OF THE OBJECTIVE FUNCTION FOR THE 3 OPTIMIZATION APPROACHES

	Spring	Summer	Autumn	Winter
MILP OF [€]	293.07	292.87	294.14	294.37
EPSO OF [€]	299.83	297.66	300.96	300.47
PSO OF [€]	386.46	316.38	332.42	354.45

Fig. 1 depicts the seasonal distribution of installed PV powers [kW] and BESS capacities [kWh], for each meter.

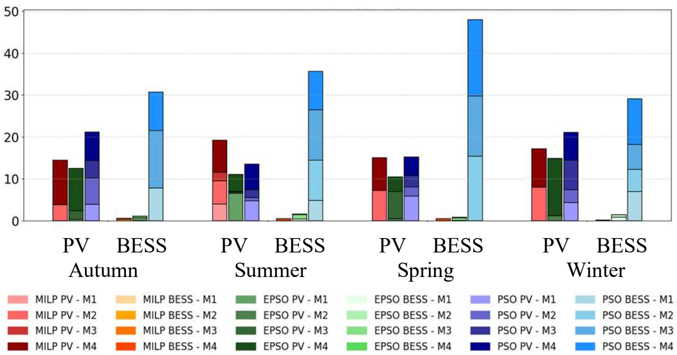

Figure 1: Comparison of installed assets [kW/kWh] per season

Fig. 2 presents the comparison of the daily member energy bills [€/day] for each season, with the methods identified by the labels M (MILP), E (EPSO), and P (PSO) in the chart.

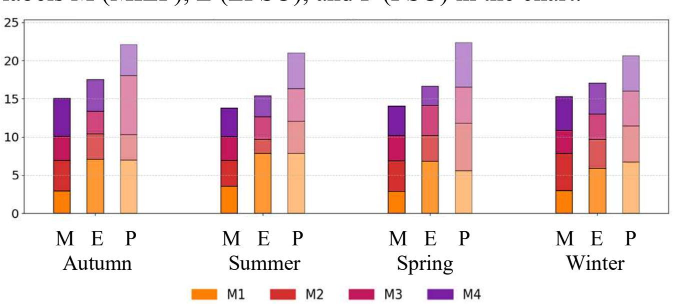

Figure 2: Comparison of member energy bills [€/day] per season

The assets allocation in the MILP approach prioritizes PV power allocation to optimize solar generation and self-consumption within the community, thereby promoting intra-community energy exchange, particularly during periods of peak solar production. This approach results in a more balanced cost distribution among the community members. Conversely, the EPSO approach allocated less PV power, compensating with a higher BESS capacity to mitigate the reduced PV output. The BESS stored energy during the morning hours is employed to address daily peak demands, thereby minimizing energy exchange among members. This strategy leads to a more imbalanced cost distribution, contingent on the timing and utilization of stored energy. Nevertheless, the allocated capacity is similar to that of the deterministic solution, making EPSO a promising approach for future research on REC asset sizing and optimization. Finally, in the PSO approach, the PV power allocation is comparable to that of the MILP approach, though it is slightly lower in the summer and slightly higher in the other seasons. However, the BESS capacity is consistently over-allocated, being at least 30 times higher than in the MILP approach, which results in inefficiencies and renders PSO the least practical option for the intended purpose.

V. CONCLUSIONS

This preliminary study aimed to evaluate the applicability of metaheuristic approaches for REC asset sizing and operation. The results indicate that while EPSO outperforms PSO, the latter demonstrates significant inefficiencies, particularly concerning the over-sizing of BESS capacity, rendering PSO unsuitable for effective REC optimization. Therefore, further exploration of PSO is not recommended. In contrast, EPSO has shown potential and warrants further investigation to enhance its performance. Future research should focus on the integration of heuristic initialization for the EWH usage term, the incorporation of battery degradation costs, and the evaluation of various pricing schemes. Additionally, optimizing the metaheuristic parameter tuning process, which currently requires an extensive trial-and-error approach, would improve the efficiency of the method. Once these aspects are addressed, EPSO can be tested in larger-scale REC systems over extended periods. In summary, while MILP remains the most robust and reliable method for asset sizing and operation at this stage, EPSO presents a promising alternative for future optimization studies.

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