A Game Theory Approach to the Multi-Objective Design of Renewable Energy Communities

Gianmarco Lorenti
Department of Energy "G. Ferraris"
Politecnico di Torino
Torino, Italy
gianmarco.lorenti@polito.it

Paolo Lazzeroni
Department of Energy "G. Ferraris"
Politecnico di Torino
Torino, Italy
paolo.lazzeroni@polito.it

Maurizio Repetto
Department of Energy "G. Ferraris"
Politecnico di Torino
Torino, Italy
maurizio.repetto@polito.it

***Abstract*—Renewable Energy Communities (RECs) are emerging as a feasible paradigm to allow the deployment of renewable-energy infrastructure, by enhancing the local production and consumption of electricity from renewable energy sources. REC design should not include only economic objectives, but also energy and environmental perspectives. These targets are often contrasting and cannot be optimized simultaneously, thus making the problem multi-objective. Traditional techniques, such as population-based metaheuristic algorithms (e.g., NSGA-II), aim to find an approximation of the Pareto front. Still, the decision-making process requires selecting a single solution, e.g., the one closest to an ideal point (Utopia) where all objectives reach their best value. In this contribution, instead, we apply an approach based on game theory to solve the multi-objective design of RECs. We draw a parallel between the objectives of the optimization problem and the players in a cooperative game. Then, the multi-objective problem is turned into a single-objective one aimed at finding the so-called Nash-bargaining solution, an equilibrium point on the Pareto front with particular symmetry properties. Considering a multifamily building, we apply this technique to the REC design including energy, environmental, and economic objectives. Comparisons with NSGA-II show how the proposed approach can find solutions on the 'compromise' area of the Pareto front, while significantly decreasing the number of objective function evaluations required, offering a computationally efficient alternative to traditional methods.**

***Index Terms*—Multi-Objective Optimization, Game Theory, Design Optimization, Renewable Energy Communities**

I. Introduction

Residential buildings significantly contribute to carbon emissions in European Union (EU) countries [1]. Despite the EU promoting energy efficiency, the environmental impact of energy consumption in buildings is still relevant, due to energy demand for space heating mostly relying on fossil fuels [2]. Sector coupling, involving high-efficiency heat pumps to electrify the heating demand, is a possible solution [3]. This strategy can achieve higher decarbonization goals when electricity comes from Renewable Energy Sources (RES).

In this context, Renewable Energy Communities (REC) can support both the decarbonization and the diffusion of distributed generation from RES, enhancing collective production and consumption of energy from RES among subjects in close proximity [4]. While RECs often involve electricity, recent research has delved into sector coupling to increase local self-consumption [5], and storage systems [6].

REC design is a complex task that considers multiple targets simultaneously (e.g., energy, economic, and environmental) [7], which are generally conflicting with each other [8], and hence it can be faced as a multi-objective optimization problem (MOOP) [5], [9], [10]. MOOPs are common in different energy fields [11], [12] when compromise solutions are needed. These problems do not have a unique solution but rather a set of non-dominated solutions, i.e., the Pareto set. These are trade-offs between the contrasting objectives where improvement in one objective function (OF) leads to the deterioration of at least one of the others. The decision process typically requires selecting a single solution among the non-dominated ones, for instance, the closest one to an ideal point (i.e., Utopia) where each objective assumes the minimum value found in the Pareto front [8].

In this contribution, instead, we adopt an approach based on game theory. Unlike traditional methods, this approach considers the objectives of the optimization problem as players in a cooperative game [13]. The MOOP is then transformed into a single-objective problem that maximizes the Nash product, which measures the distance from a disagreement point where each player gets the worst payoff [14] This method already yields a Pareto-efficient solution with particular symmetry properties, avoiding the need to explore the entire Pareto front.

In this work, we demonstrate the application of the game theory-based approach for multi-objective design in a case study involving a multifamily building with sector coupling and storage systems, optimizing for energy, environmental, and economic objectives. We compare the proposed method with traditional approaches like NSGA-II, highlighting its advantages in terms of solution quality and computational efficiency. By analyzing two different setups with an increasing number of objectives, we show the feasibility of the proposed approach and, possibly, its superiority in higher dimensions, where the concept of non-dominance becomes less resolutive.

The rest of the paper is organized as follows: we present the REC layout and multi-criteria assessment in II; in III we describe the methods used in the REC design with traditional multi-objective optimization and with proposed approach based on game theory; in IV we detail the case study and analysis conducted; in V we analyze the obtained results and in VI we conclude this work.

II. Modeling and Assessment

A. Collective self-consumption

RECs are energy systems involving multiple subjects, located close to each other, who can produce, consume, and collectively share electricity from RES. Energy sharing between REC members is *virtual*: they exchange electricity with the public distribution grid through their point of delivery (POD); then, shared energy is *calculated* as the minimum between the total injections and withdrawals (in Italy, in each hour).

The term "collective self-consumption" is used when REC members are in the same building. For instance, residential end users in a multifamily building can install a photovoltaic system (PV) on the building's rooftop to supply shared loads. Overgeneration is injected into the grid at the building's POD and can be shared by the households virtually.

This paper considers the multi-energy REC layout depicted in Fig. 1: the electricity produced by the PV is used to feed a heat pump (HP) before being injected into the grid; the HP supplies the centralized heating demand during the winter season, together with a gas-fired boiler (BOIL); a battery energy storage system (BESS) and a heat storage system (HSS) provide further flexibility to the REC.

B. Power and energy balances

The following electric and thermal power balances hold for the building in Fig. 1:

$$P_{\mathrm{pv}} + P_{\mathrm{bess,d}} + P_{\mathrm{with}} = P_{\mathrm{hp,el}} + P_{\mathrm{bess,c}} + P_{\mathrm{inj}}, \tag{1}$$

$$P_{\mathrm{hp,th}} + P_{\mathrm{hss,d}} + P_{\mathrm{boil,th}} = P_{\mathrm{ut,agg}} + P_{\mathrm{hss,c}}, \tag{2}$$

where, P is a uniform average power in the time step of length $\Delta t_{\mathrm{h}} = 1$ h. The subscripts are detailed in Tab. I.

The energy shared in the REC can then be calculated as:

$$E_{\mathrm{sh}} = \min\left(P_{\mathrm{inj}}\Delta t_{\mathrm{h}}, P_{\mathrm{ue,agg}}\Delta t_{\mathrm{h}}\right). \tag{3}$$

Consequently, the REC *virtually* exchanges with the grid:

$$E_{\mathrm{to\,grid}} = P_{\mathrm{inj}}\Delta t_{\mathrm{h}} - E_{\mathrm{sh}}, \tag{4}$$

$$E_{\mathrm{from\,grid}} = \left(P_{\mathrm{with}} + P_{\mathrm{ue,agg}}\right)\Delta t_{\mathrm{h}} - E_{\mathrm{sh}}. \tag{5}$$

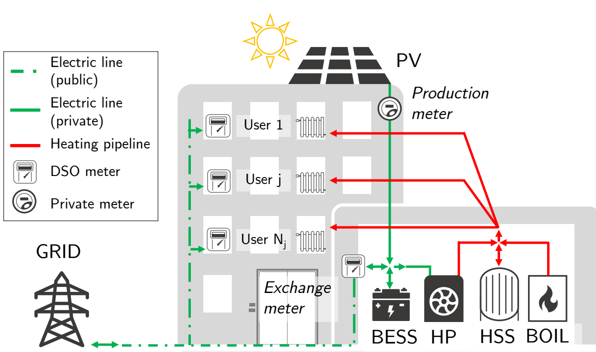

Fig. 1. Layout of the multi-energy REC in a residential building.

TABLE I
Subscripts in power and energy balances.

Subscript	Meaning
pv	PV electric output
bess,c / bess,d	BESS charge/discharge power
inj / with	Grid injection/withdrawal from the building's POD
hp,el / hp,th	HP electric input and thermal output
boil,gas / boil,th	Gas-fired boiler gas input and thermal output
hss,c / hss,d	HSS charge and discharge power
ue,agg / ut,agg	Households' aggregated electric and heating loads
sh	Virtually shared electricity
to grid / from grid	Net virtual electricity exchanges with the grid

C. Power and energy flows optimization

Flexibility sources in the REC (like coupling -HP- and storage components -BESS and HSS-) result in a complex energy system [8]. We use Linear Programming (LP) to identify the optimal REC operation (i.e., power and energy flows) in all hourly time steps of a reference year with given RES generation and electricity and heating load profiles. The previous balance equations and the constitutive equations of the components define the constraints, while the objective is the minimization of the operation costs of the REC. Detailed formulation and software implementation can be found in [8][1].

D. Key Performance Indicators

REC performances can be evaluated using Key Performance Indicators (KPIs) considering multiple points of view, e.g., those employed in [8] and described in the following.

Energy KPIs include self-consumption (SC) and self-sufficiency (SS), which are the ratios of electricity consumed locally (physically and virtually) over total PV production and REC consumption respectively, and are evaluated as follows:

$$\mathrm{SC} = 1 - \frac{E_{\mathrm{to\,grid}}}{E_{\mathrm{pv}}}, \tag{6}$$

$$\mathrm{SS}_{\mathrm{el}} = 1 - \frac{E_{\mathrm{from\,grid}}}{E_{\mathrm{with}} + E_{\mathrm{ue,agg}}}. \tag{7}$$

To assess the REC from the environmental and economic points of view, we compare it with the base case, where the building energy needs are fulfilled by relying exclusively on the grid ($E^{(0)}_{\mathrm{from\,grid}}$) and gas-fired boiler ($E^{(0)}_{\mathrm{boil,gas}}$).

We evaluate the CO_2 emissions (EM) of the REC and in the base case, and then the emissions reduction (ER), as follows:

$$\mathrm{EM} = \mathrm{EM}_{\mathrm{LCA}} + E_{\mathrm{from\,grid}}\epsilon_{\mathrm{grid}} + E_{\mathrm{boil,gas}}\epsilon_{\mathrm{gas}}, \tag{8}$$

$$\mathrm{EM}^{(0)} = E^{(0)}_{\mathrm{from\,grid}}\epsilon_{\mathrm{grid}} + E^{(0)}_{\mathrm{boil,gas}}\epsilon_{\mathrm{gas}}, \tag{9}$$

$$\mathrm{ER} = \frac{\mathrm{EM}^{(0)} - \mathrm{EM}}{\mathrm{EM}^{(0)}}, \tag{10}$$

where, $\mathrm{EM}_{\mathrm{LCA}}$ includes life-cycle emissions of the installed components [8], while ϵ_{grid} and ϵ_{gas} are the CO_2 emission factors in $\mathrm{kg}_{\mathrm{CO_2,eq}}/\mathrm{kWh}$ of grid electricity and gas consumption.

[1]In [8], the authors used mixed integer LP. The LP formulation is obtained by removing binary variables and omitting or simplifying the related constraints. A posterior check verifies that the latter are still satisfied.

We consider total actualized costs (TAC) [5], which can be calculated as follows:

$$\mathrm{TAC} = C_{\mathrm{capex}} - C_{\mathrm{res}} + \sum_{\mathrm{t}=1}^{\mathrm{N}} \frac{1}{(1+r)^t} \left(C_{\mathrm{opex}} + C_{\mathrm{energy}} \right) \quad (11)$$

where, N is the project lifetime and r the discount factor; C_{capex} includes purchase and installation costs; C_{res} considers any residual value of the technologies at the end of their lifetime; C_{opex} includes insurance and maintenance costs; and C_{energy} considers yearly energy expenditures and incomes, evaluated according to REC regulation (see [4], [8]):

$$\begin{aligned} C_{\mathrm{energy}} = & \left(E_{\mathrm{with}} + E_{\mathrm{ue,agg}} \right) c_{\mathrm{with}} + E_{\mathrm{boil,gas}} c_{\mathrm{gas}} \\ & - \left(E_{\mathrm{inj}} c_{\mathrm{inj}} + E_{\mathrm{sh}} c_{\mathrm{sh}} \right), \end{aligned} \quad (12)$$

where, $\mathrm{c_{with}}$ and $\mathrm{c_{gas}}$ are the grid electricity and gas prices, $\mathrm{c_{inj}}$ and $\mathrm{c_{sh}}$ the market price of electricity and the incentive for shared energy, respectively.

Costs reduction (CR) is then evaluated similarly to (10), by comparing TAC in the REC and base case, where only energy costs are present, calculated considering $E^{(0)}_{\mathrm{from\ grid}}$ and $E^{(0)}_{\mathrm{boil,gas}}$ with their related prices.

III. Multi-Objective Design

The previous KPIs typically exhibit contrasting trends [8], and therefore the REC design considering these targets is a multi-objective optimization problem.

A. Multi-objective optimization problem

These problems are usually formulated as follows [15]:

$$\begin{aligned} & \min_{\mathbf{x} \in X} \left(f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_{\mathrm{m}}(\mathbf{x}) \right) \\ \text{s.t.} \quad & g_{\mathrm{j}}(\mathbf{x}) \leq 0 \quad (j = 1, \dots, q) \ , \\ & h_{\mathrm{k}}(\mathbf{x}) = 0 \quad (k = 1, \dots, p) \end{aligned} \quad (13)$$

where, $\mathbf{x}$ is the vector of design variables (i.e., the sizes of the installed components in a design optimization problem), X is the design space, and $f_1, \cdots, f_{\mathrm{m}}$ are the objective functions.

The solution to a MOOP is not unique as it consists of a set of non-dominated solutions, the so-called Pareto set -or Pareto Front considering their images in the objectives space-, where improving one objective function leads to the deterioration of at least one of the others. Population-based metaheuristic algorithms are commonly used to find approximated Pareto fronts [15]. For instance, NSGA-II [16] is a popular genetic algorithm based on non-dominated sorting that generates and iteratively updates a population of solutions until a termination criterion is met.

Once the Pareto set is identified, the decision-making process typically continues, to select a single compromise solution between the contrasting objectives. For instance, two relevant points can be derived from the Pareto front: the Utopia (ideal) and Nadir, combining each objective's minimum and maximum values within the Pareto front, respectively (see Fig. 2). Then, a compromise solution can be selected to minimize the distance from the Utopia point [8] or maximize the distance from Nadir.

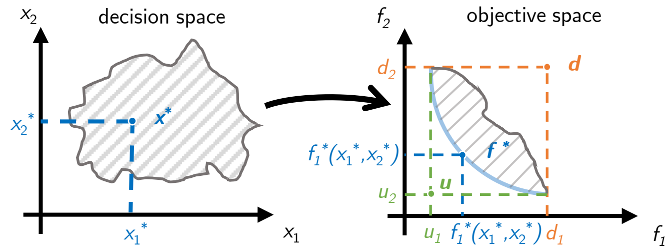

Fig. 2. Example of Nash-bargaining solution, Utopia, and Nadir points, in a bi-objective optimization problem with two decision variables.

B. MOOP and game theory

In this paper, we apply an alternative approach, based on game theory, that considers a MOOP equivalent to a cooperative game, as suggested by [13], where:

- Each OF f_{i} is associated with a player as its utility function.
- A feasible solution $\mathbf{x} \in X$ represents a possible agreements point between players.
- Each player's payoff in a certain agreement point corresponds to the value of the related objective.

In this view, a bargaining solution can be evaluated, also called Nash-bargaining [17], [18]. This point is located on the Pareto front, i.e., non-dominated. Moreover, it has particularly desirable symmetry properties, as it is the point where each target is as distant as possible from its worst value. The Nash-bargaining solution ($\mathbf{x}_{\mathrm{NB}}$) is obtained by maximizing the Nash product, as follows [14]:

$$\begin{aligned} & \mathbf{x}_{\mathrm{NB}} = \arg \max_{\mathbf{x} \in X} \prod_{i=1}^{m} \left(d_{\mathrm{i}} - f_{\mathrm{i}}(\mathbf{x}) \right) \\ & \text{s.t.} \quad f_{\mathrm{i}}(\mathbf{x}) \leq d_{\mathrm{i}} \quad \forall i = 1, \dots, m \end{aligned} \quad (14)$$

with $d \left(d_1, d_2, \cdots, d_m \right)$ being a disagreement point where all players obtain their worst payoff due to the absence of a mutual agreement. In particular, we consider the pseudo-Nadir point, evaluated as described after. An example of the Nash-bargaining solution is shown in Fig. 2, in both the decision and objective spaces, considering a bi-objective optimization problem with two design variables.

The proposed approach consists of the following steps:

1) Identify the coordinates in the design space of the Utopia point, by optimizing the single objectives individually:
$$\mathbf{x}_{\mathrm{U,i}} = \arg \min_{\mathbf{x} \in X} f_{\mathrm{i}}(\mathbf{x}) \quad \forall i = 1, \dots, m \quad (15)$$
2) Evaluate the pseudo-Nadir point, by combining the worst solution for each objective:
$$d_{\mathrm{i}} = \max_{\mathrm{j} \neq \mathrm{i}} f_{\mathrm{i}}(\mathbf{x}_{\mathrm{U,j}}) \quad \forall i = 1, \dots, m. \quad (16)$$
3) Calculate the Nash-bargaining solution solving (14) using the previous disagreement point.

Globally, the proposed approach requires solving one single-objective optimization problem for each objective to find the Utopia point (and, consequently, the pseudo-Nadir), and one for the Nash-bargaining solution.

IV. Case Studies

The REC considered in this paper is a fictitious multifamily building in Northern Italy with 40 households. A detailed description of the case study, the input data, and the environmental and economic parameters can be found in [4] and [8].

To simplify the LP problem, which in the full reference year consists of roughly 1.1×10^5 variables and 1.5×10^5 constraints, we solve the optimize *separately* 24 typical days, identified using KMeans clustering on the input quantities in each hour of the day (RES generation, aggregate electricity and heating loads) [19]. REC assessment is performed using the in-house tool `Recoupled` [8], which relies on the commercial solver `Gurobi` [20] to solve the LP problem.

In the following section, we compare the game theory approach described in III with the traditional multi-objective approach based on finding an approximation of the Pareto front, e.g., through population-based *metaheuristic* algorithms. We present the results for two different setups, where the number of objectives in the MOOP increases while keeping the same design space (see Tab. II). In the latter case, since the concept of non-dominance becomes less resolutive when the number of objectives increases, algorithms like NSGA-II may require a larger population to converge, resulting in higher computational times or lower quality (if the number of objective function evaluations is bounded).

The MOOP was solved using the NSGA-II implementation from `pymoo` [21], setting default values of the hyperparameters and termination criterion (including a maximum number of objective function evaluations equal to 1×10^5). We used Pattern Search (PS), a simple and well-known algorithm, to solve the single objective optimization problems required by the game theory approach, using the implementation available in `pymoo`, again setting default values. In all cases, the problem was constrained to avoid solutions with positive objectives (given the sign inversion), which are considered here as unfeasible (e.g., negative cost reduction).

Since NSGA-II returns the final population of non-dominated individuals approximating the Pareto front, we base our comparison on two points that characterize the extremes of the front, i.e., Utopia and Nadir. Furthermore, we compare the Nash-bargaining solution with the compromise solution evaluated from the Pareto set as the one minimizing the distance from the Utopia point (with normalized objectives):

$$\mathbf{x}_{\text{closest}} = \arg\min_{\text{x}\in\text{P}} \sum_{\text{i}=1}^{\text{m}} \left(\frac{f_{\text{i}}(x) - u_{\text{i}}}{d_{\text{i}} - u_{\text{i}}} \right)^2, \tag{17}$$

TABLE II
Design space and objective functions in the different setups.

<table>
<tr><th>Setup</th><th colspan="2">Design variables and space</th><th>Objective functions</th></tr>
<tr><td>1</td><td rowspan="2">PV
HP
BESS
HSS</td><td rowspan="2">$[10, 70]$ kW$_\text{p}$
$[0, 180]$ kW$_\text{th}$
$[0, 100]$ kWh
$[0, 200]$ kWh</td><td>$-$CR, $-$ER</td></tr>
<tr><td>2</td><td>$-$CR, $-$ER, $-$SC, $-$SS$_\text{el}$</td></tr>
</table>

where, P is the final Pareto set, and $u = (u_1, \ldots, u_\text{m})$ and $d = (d_1, \ldots, d_\text{m})$ are, respectively, the Utopia and Nadir points evaluated by NSGA-II.

V. Results

A. Two objectives

Fig. 3 represent in the objectives space the Pareto front obtained executing NSGA-II with a population of 250 individuals and the points obtained with the game theory approach. The figure shows that the extremes of the Pareto front found by NSGA-II do not necessarily overlap with those found by the single-objective optimizations. Consequently, the Utopia and pseudo-Nadir points do not coincide. This indicates that the front found by NSGA-II is not complete on the extremes. It should be noted that the algorithm stopped before reaching a maximum number of OF evaluations, hence determined by the convergence of the Pareto front and set. Furthermore, we can notice that, as expected, the Nash-bargaining solution lies on the Pareto front, located on the knee region of the front (where fair trade-offs between the objectives are expected to be found), in proximity to the closest point to the Utopia found by NSGA-II. The two points are not supposed to coincide, since they originate from different objective functions (see III).

Fig. 4 shows the evolution of the coordinates of the points of interest (Utopia, Nadir, closest to Utopia, and Nash-bargaining) with the number of OF evaluations of the two algorithms. The Utopia and Nadir values found by the single objective optimization are also shown as references (dash-dotted lines). It is interesting to highlight the different number of objective function evaluations required for the Nash-bargaining problem to converge stably (one order of magnitude smaller than NSGA-II). Conversely, the point closest to Utopia found by NSGA-II shows slight variations, even after the extreme points stabilize, as the Pareto front keeps varying.

B. Four objectives

As the representation of the objective space is not trivial with more than two objectives, we focus solely on the points of interest described before and, specifically, their convergence with the number of objective function evaluations. Due to the

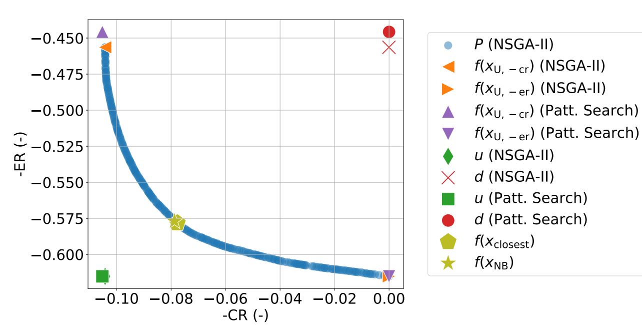

Fig. 3. Points in the objectives space found by NSGA-II and the game theory approach in the two-objective problem.

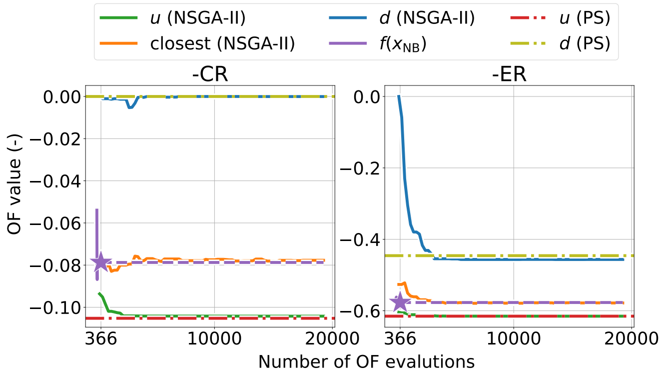

Fig. 4. Convergence of NSGA-II and the game theory approach with the number of OF evaluations in the two-objective problem. The Nash-bargaining solution is shown even after convergence (dashed line) for comparison, while the number of OF evaluations at termination is highlighted with a marker. The OF values are dimensionless since related to the KPIs described in II.

higher dimension of the objective space, we executed NSGA-II with a population of 2500 individuals to guarantee a proper convergence. It should be noted that, differently from the previous case, the algorithm was terminated by the maximum number of objective function evaluations (equal to 1×10^5). Fig. 5 shows, in general, that the convergence of NSGA-II to stable extreme points requires more evaluations than before, whereas those required to find the Nash-bargaining solution remain significantly smaller. Again, the coordinates of the point closest to Utopia (orange curve) vary during the execution of NSGA-II, reflecting the continuous change of the solutions that compose the population. Moreover, in this case, the oscillations of the coordinates of this point are more significant, indicating a higher variation, and hence a worse convergence of the NSGA-II algorithm.

A relevant highlight concerns the coordinates of the Nadir point found by NSGA-II and the pseudo-Nadir evaluated from the Utopia point, as described in III. In particular, since the values of the single objectives are smaller in the second case, the pseudo-Nadir underestimates the worst case for the objectives. Still, the figure shows that the Nash-bargaining solution found using this disagreement point lies relatively close to the (oscillating) point closest to Utopia, reflecting how this solution lies in a knee region of the Pareto front.

Tab. III reports the numerical results in the two setups, at the final iteration of each algorithm, to enhance clarity.

C. Stability of the algorithms

Tab. IV shows the convergence of the Nash-bargaining solution in 10 different executions of the Pattern Search solver in the two setups. In the first setup, with two objectives, all the executions converge to the same objective function value (i.e., for the Nash product). Moreover, the convergence is reached on average after 366 OF evaluations, with a small deviation between minimum and maximum values. When considering the case with four objectives, we notice that a higher number of OF evaluations is generally required for the algorithm to stabilize. Furthermore, at least one execution stopped at a lower objective value, as the algorithm ended up in some local maximum. This is possible since PS is not a global optimizer.

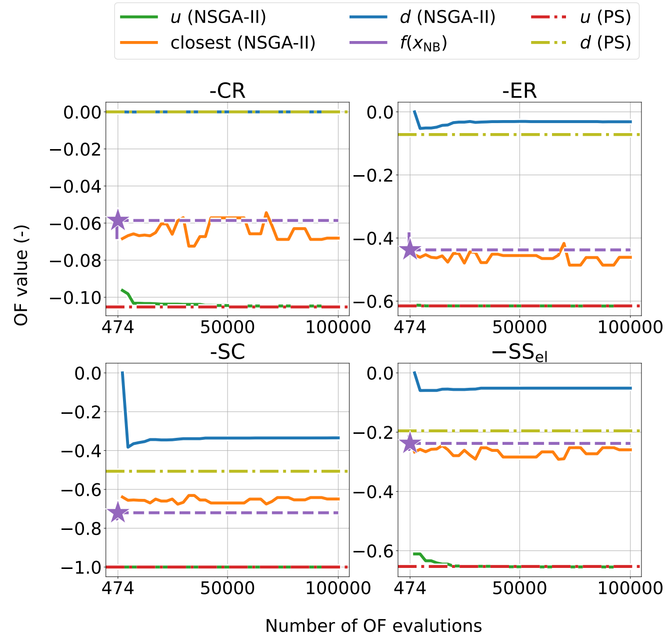

Fig. 5. Convergence of NSGA-II and the game theory approach with the number of OF evaluations in the four-objective problem. The Nash-bargaining solution is shown even after convergence (dashed line) for comparison, while the number of OF evaluations at termination is highlighted with a marker. The OF values are dimensionless since related to the KPIs described in II.

VI. Conclusion

In this work, we addressed the design of a Renewable Energy Community (REC) for households in a multifamily building aiming to reduce their reliance on the electricity grid and gas by installing renewable-based and flexibility assets. The REC design, i.e., sizing the components such as a photovoltaic system, heat pump, battery energy storage system, and heat storage system, was framed as a multi-objective optimization problem (MOOP) with contrasting energy, environmental, and economic targets.

Specifically, we adopted an approach based on game theory, treating the multi-objective design problem as a cooperative game where each objective represents a player. A compromise solution (Nash-bargaining) was found by maximizing the Nash-product, which measures the distance between the equilibrium point and a disagreement point where each player gets the worst payoff. Unlike traditional approaches, this method simplifies the MOOP by solving a series of single-objective optimizations to find the disagreement point and the Nash-bargaining solution.

We compared the proposed approach with the traditional method consisting of approximating the Pareto front, using NSGA-II, and selecting a compromise point. In particular, we selected the point in the Pareto front closest to the Utopia point, obtained by combining the minimum value of each objective. We considered two setups, with two and four

TABLE III
RESULTS OBTAINED IN THE TWO SETUPS WITH TWO APPROACHES. THE VALUES OF THE OFS AT THE LAST ITERATION ARE REPORTED.

Setup	Approach	Utopia				Nadir				Closest to Utopia/Nash-bargaining			
		-CR	-ER	-SC	-SS	-CR	-ER	-SC	-SS	-CR	-ER	-SC	-SS
1	NSGA-II	-0.104	-0.615	-	-	0	-0.456	-	-	-0.078	-0.578	-	-
	Game theory	-0.105	-0.615	-	-	0	-0.445	-	-	-0.079	-0.577	-	-
2	NSGA-II	-0.105	-0.616	-1	-0.655	0	-0.031	-0.334	-0.051	-0.068	-0.461	-0.649	-0.259
	Game theory	-0.105	-0.615	-1	-0.653	0	-0.072	-0.507	-0.195	-0.059	-0.438	-0.720	-0.238

TABLE IV
CONVERGENCE STATISTICS OVER 10 EXECUTIONS OF NASH-BARGAINING OPTIMIZATION FOR THE TWO SETUPS.

Setup	Number of OF evaluations			OF value at convergence		
	Min	Median	Max	Min	Median	Max
1	334	366	400	0.010315	0.010315	0.010315
2	360	417	645	0.001289	0.001297	0.001297

objectives, as the concept of non-dominance becomes less resolutive in higher-dimensional objective spaces.

In both setups, our approach found a point on the knee region of the Pareto front, where compromises between objectives are located. The number of objective function evaluations was significantly reduced compared to NSGA-II, which requires finding the entire front. While the extreme points of the Pareto front found by NSGA-II stabilized, the closest point to Utopia continued to vary, especially in the second setup, resulting in different solutions depending on where the algorithm is stopped. Conversely, our approach showed consistent performance across multiple executions. However, using Pattern Search led to local optima in some executions of the second setup, indicating the need for a global optimizer.

Future work will focus on analyzing algorithm convergence across different executions and exploring alternative solvers to address the need for a global optimizer with more complex objective functions. Additionally, we will test the game theory approach with various combinations of objectives, eventually increasing their number towards a many-objective approach.

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