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Community-Based Energy Sharing using Game Theory Approaches for Benefit Distribution

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***Abstract*—This paper is centered on the concept of community-based energy sharing, focusing on the integration of electric vehicles and battery management systems. The study employs mixed integer linear programming optimization techniques to minimize the total energy costs of the entire community by maximizing energy sharing within it. The investigation focuses on exploring methods of distribution of benefits among community members considering BESS and EV demand. The paper explores the mid-market rate, supply-demand rate, Shapley value, and Nucleolus analysis as methods to distribute the benefits generated by the energy community. The analysis contributes to understanding how community-based energy sharing can vary depending on the distribution method. Moreover, the study presents two scenarios with a community of up to 20 agents: PV generation without batteries and PV with batteries, both considering forecasted EV demand. The influence of transactions in the energy community allows for a cost-benefit of around 6% to 13%. When batteries are considered, the costs are reduced by up to 16%. The benefit distribution schemes are also investigated, and their excess is analyzed for each case.**

***Index Terms*—batteries, benefit distribution, electric vehicles, energy communities, game theory**

I. Introduction

Today's electric power systems are undergoing several changes, from a centralized production manner, where there is only a unidirectional flow of electricity, to a decentralized production manner, with the integration of distributed energy resources, with a bidirectional flow of electricity. Due to this increasing integration, and with electricity grid players becoming more active with local production for system flexibility (prosumers), the term local energy communities (LEC) [1], also referred to in some cases as local electricity markets (LEM) or renewable energy communities [2], is emerging with a large interest in the energy field, where in the European Union they were first introduced in the "Clean energy for all Europeans package" [3].

Multiple residencies normally constitute a LEC in a building or multiple buildings in a 2 km radius connected to the same feeder in low voltage. This criterion enables energy sharing between players when there is a local overproduction at more competitive prices than those imposed by the grid operators to increase community profits through market-based models or cost/benefit-sharing models [4], [5]. Concerning market-based models, LEM and peer-to-peer (P2P) are normally considered trading mechanisms inside the community. Concerning LEM, in [4], different LEM pricing strategies are implemented for different information exchange designs in the community, where some fair pricing indicators are incorporated, such as the quality of service and experience and minimum-maximum indicators. A benefit maximization approach is proposed in [6], where electric vehicles (EVs) are considered for each household, and the LEM price is based on the total community supply and demand. When it comes to P2P [7] presents an optimal P2P model considering battery storage systems and a mid-market rate (MMR) is implemented as a pricing strategy for the P2P price, [8] considers battery and hydrogen vehicles together with BSS in P2P trading and [9] compares a centralized and distributed P2P market approach, trough the alternating direction method of multipliers (ADMM), where BSS are integrated and user prices are compared in the LEC.

Concerning cost/benefit-sharing models, which in comparison are more simple to implement, [10] shows a coalition game for benefit sharing in an LEC where the Shapley value is implemented, and a clustering mechanism is used to cluster user profiles. In [11] introduces a post-process benefit-sharing approach based on multiple pricing strategies, such as MMR, supply-demand rate (SDR), and others, that ensures benefits for prosumers who participate in the energy community, that

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is, the users only reduce their electricity bill, not the other way around.

In this work, multiple benefit distributions are analyzed, considering different LEC pricing mechanisms such as MMR and SDR and comparing these benefits with fairer approaches, like the Shapley value (SV) and Nucleolus [12] based on a game-theoretic approach where all the possible coalitions inside the community are made taking [13] as a starting point. Simulations are made up of 20 agents in the community, considering different scenarios related to the inclusion of the operation of battery storage systems (BSS), where in some scenarios, these are considered for some agents.

The present work is organized as follows: after introducing the topic and contributions of this work in Section I, the mathematical formulation regarding the local energy communities and a game theoretic approach is presented in Section II, together with BES operation optimization. Section III describes the formulation encompassing different benefit distribution strategies, with the considered LEC case study and different proposed scenarios shown in Section IV. Section V gives this work's results concerning the LEC benefit distribution in the different scenarios, and Section VI presents the main conclusions and possible future work.

II. Local energy communities

A LEC $\mathcal{N}$ comprises i agents, which have PV panels for autoconsumption and, in other scenarios, have BSS and EVs associated. The net consumption and net generation of each agent can be computed as $\lambda_{i,t}^{nc} = max(\lambda_{i,t}, 0)$ and $\lambda_{i,t}^{ng} = min(\lambda_{i,t}, 0)$, respectively. The cost of each user without participation in the energy community, where energy sharing between agents is not possible, can be given by [13]:

$$Cost_i = \sum_{t \in T} (s_t^{\text{buy}} \cdot \lambda_{i,t}^{nc} + s_t^{\text{sell}} \cdot \lambda_{i,t}^{ng}) \; \forall i \in N \tag{1}$$

where:

$$\lambda_{i,t} = p_{i,t}^{\text{load}} - p_{i,t}^{\text{gen}} + b_{i,t}^{\text{ch}} - b_{i,t}^{\text{dch}} + \sum_{k \in K} vh_{i,k,t}^{\text{ch}} \; \forall i \in N \; \forall t \in T \tag{2}$$

Where $b_{i,t}^{\text{ch}}$ and $b_{i,t}^{\text{dch}}$ represent the decision variables of charge and discharge of each BES i at period t. In this case, if $\lambda_{i,t}$ is less than 0, there is a net production, and the users will sell their surplus to the grid. Otherwise, they need to buy from the grid. When an energy community is formed, and energy surplus can be exchanged, the energy cost can be calculated as follows:

$$Cost_{\mathcal{N}} = \sum_{t \in T} (s_t^{\text{buy}} \cdot \sum_{i \in \mathcal{N}} \lambda_{i,t}^{nc} + s_t^{\text{sell}} \cdot \sum_{i \in \mathcal{N}} \lambda_{i,t}^{ng}) \tag{3}$$

This results in a total community benefit:

$$v(\mathcal{N}) = \sum_{i \in \mathcal{N}} Cost_i - Cost_{\mathcal{N}} \tag{4}$$

A. Game theory

Local energy communities can be represented as a cooperative game, where agents act as players collaborating to optimize both the overall and individual benefits they receive. As such, inside the energy community, many sub-communities between agents can be made, which are named coalitions (S) [14]. The number of all possible coalitions is $2^{\mathcal{N}}$. Similarly to Eq. (4), the benefit inside a subset can be given as:

$$v(S) = \sum_{i \in S} Cost_i - Cost_S \tag{5}$$

In this case, $v : 2^{\mathcal{N}} \rightarrow \Re$, mapping the coalition to a real number. Computing coalition benefits an allocation vector x_i of the payoffs can be obtained from a distribution strategy. Given this allocation, the excess of a coalition is formulated as follows:

$$e(x, S) = v(S) - \sum_{i \in S} x_i \tag{6}$$

The excess represents the satisfaction of a coalition. If $e(x, S) \geq 0$, the coalition S receives greater benefits on its' own than inside the community. Otherwise, the coalition has no reason to leave the community.

B. Otimization model considering batteries

When technologies such as EVs and BES are considered, a scheduling optimization model must be implemented. The total energy cost is then minimized through BES operation in each coalition. The mathematical formulation of the model based on [14] is:

$$min \; Cost_S = \sum_{t \in T} (s_t^{\text{buy}} \cdot \sum_{i \in S} \lambda_{i,t}^{nc} + s_t^{\text{sell}} \cdot \sum_{i \in S} \lambda_{i,t}^{ng}) \tag{7}$$

s.t.

$$\lambda_{i,t}^{nc} \leq im_i \; \forall i \in S \; \forall t \in T \tag{8}$$

$$|\lambda_{i,t}^{ng}| \leq ex_i \; \forall i \in S \; \forall t \in T \tag{9}$$

$$b_{i,t}^{\text{ch}} \leq b_i^{\text{chMax}} \cdot x_{i,t}^{\text{ch}} \; \forall i \in S \; \forall t \in T \tag{10}$$

$$b_{i,t}^{\text{dch}} \leq b_i^{\text{dchMax}} \cdot x_{i,t}^{\text{dch}} \; \forall i \in S \; \forall t \in T \tag{11}$$

$$x_{i,t}^{\text{ch}} + x_{i,t}^{\text{dch}} \leq 1 \; \forall i \in S \; \forall t \in T \tag{12}$$

$$soc_{i,t}^{\text{bat}} = soc_{i,t-1}^{\text{bat}} + \eta_f^{\text{bat}} \cdot b_{i,t}^{\text{ch}} - \frac{1}{\eta_f^{\text{bat}}} \cdot b_{i,t}^{\text{dch}} \; \forall i \in S \; \forall t \in T \tag{13}$$

$$soc_i^{\text{minCap}} \leq soc_{i,t}^{\text{bat}} \leq soc_i^{\text{maxCap}} \; \forall i \in S \; \forall t \in T \tag{14}$$

$$soc_{i,T}^{\text{bat}} \geq soc_i^{\text{bEnd}} \; \forall i \in S \tag{15}$$

Where $x_{i,t}^{\text{ch}}$ and $x_{i,t}^{\text{dch}}$ are binary variables that represent the state of the BES, and the state-of-charge of each BES is represented by the $soc_{i,t}^{\text{bat}}$ decision variable. If any prosumer has no BES, the values are set to zero, and the balance in Eq. (2) is calculated accordingly.

III. Benefit distribution strategies

When energy sharing is an option and grid transactions are minimized, different benefit distribution schemes must be considered inside a LEC concerning each individual user. In this work, four different benefit strategies are used and compared. Two of those are based on different pricing schemes (MMR and SDR). The other two are an equal benefit split between community members, where each member receives an equal benefit (not fair), and the Shapley value, a fair distribution method based on the marginal contribution of each member.

A. Mid-market rate

The MMR pricing strategy [15] is an average price between the time-of-use and the feed-in tariffs. So the selling price for agents with an overproduction, when the total community balance is positive, is now given by:

$$s_t^{\text{mid}} = \frac{s_t^{\text{buy}} + s_t^{\text{sell}}}{2} \; \forall t \in T \tag{16}$$

In contrast, for the agents with a positive net consumption, the buying price is now:

$$s_t^{mbuy} = \frac{s_t^{\text{mid}} \cdot |\sum_{i\in\mathcal{N}} \lambda_{i,t}^{ng}| + s_t^{\text{buy}} \cdot \sum_{i\in\mathcal{N}} \lambda_{i,t}}{\sum_{i\in\mathcal{N}} \lambda_{i,t}^{nc}} \; \forall t \in T \tag{17}$$

When the total community balance is negative, the agents with a positive net consumption buy energy at s_t^{mid} and the agents with a net generation sell their energy according to:

$$s_t^{msell} = \frac{s_t^{\text{mid}} \cdot \sum_{i\in\mathcal{N}} \lambda_{i,t}^{nc} + s_t^{\text{sell}} \cdot |\sum_{i\in\mathcal{N}} \lambda_{i,t}|}{|\sum_{i\in\mathcal{N}} \lambda_{i,t}^{ng}|} \; \forall t \in T \tag{18}$$

B. Supply-demand rate

The SDR pricing [4] strategy sets the internal community price according to a ratio between the community net generation and net demand, formulated as follows:

$$r_t^{\text{sdr}} = \frac{|\sum_{i\in\mathcal{N}} \lambda_{i,t}^{ng}|}{\sum_{i\in\mathcal{N}} \lambda_{i,t}^{nc}} \; \forall t \in T \tag{19}$$

$$s_t^{\text{sdr}} = \begin{cases} s_t^{\text{sell}}, & \text{if } r_t^{\text{sdr}} \geq 1 \\ s_t^{\text{buy}}, & \text{if } r_t^{\text{sdr}} = 0 \\ r_t^{\text{sdr}} \cdot s_t^{\text{sell}} + (1 - r_t^{\text{sdr}}) \cdot s_t^{\text{buy}}, & \text{otherwise} \end{cases} \; \forall t \in T \tag{20}$$

In Eq. (20), if the total net generation exceeds the total net consumption, the price equals the feed-in tariff. If there is no net generation, where the ratio is zero, the price equals the time-of-use tariff. Otherwise, the price is settled as a convex combination of the ratio between the time-of-use and feed-in tariffs.

C. Shapley value

In game theory, the SV distributes the benefits among players based on their marginal contribution. It assesses the significance of each player i in a game by calculating a weighted average of their marginal contributions across all potential coalitions they can join. The benefit of each player can then be calculated as follows [16]:

$$s_i^{SV} = \sum_{S\subseteq\mathcal{N}\setminus\{i\}} \frac{|S|!(|\mathcal{N}| - |S| - 1)!}{|\mathcal{N}|!} \cdot (v(S\cup\{i\}) - v(S)) \tag{21}$$

The significance of the Shapley value is that it is considered a fair method since it meets these four different criteria:

- *additivity*: $s_i(v + w) = s_i(v) + s_i(w)$;
- *efficiency*: $v(\mathcal{N}) = \sum_{i\in\mathcal{N}} s_i$;
- *null player*: $v(S\cup\{i\}) - v(S) = 0, \; \forall S \subseteq \mathcal{N}\setminus\{i\} \rightarrow s_i = 0$;
- *symmetry*: $v(S\cup\{i\}) = v(S\cup\{j\}), \; \forall S \subseteq \mathcal{N}\setminus\{i\} \rightarrow s_i = s_j$.

In *additivity*, the combined value of two games equals the sum of their individual values. Applied to LEC, it means that in a coalition playing a composite game, each agent's benefit is the sum of benefits from each game. The *efficiency* dictates that the benefits of all the agents in the grand coalition equals the sum of the agents' Shapley value (distributed among all agents). Agents with a marginal contribution of zero receive no benefits in the *null player* criteria, and the *symmetry* criteria states that if two players have the same marginal contribution to every coalition, they receive the same benefit.

D. Nucleolus

In a cooperative game, the Nucleolus is the lexicographically minimum imputation that reduces player dissatisfaction, represented in Eq. (6). By defining the excess vector $\epsilon(x) = e(x, S_j) \in K\backslash N, \forall j = 1, ..., 2^N - 2$, the Nucleolus can be obtained by a series of linear programming optimization models where $\epsilon(x)$ $(min \;\; max \;\; \epsilon)$ is minimized [17]. The Nucleolus is a stabilizing imputation because it always exists and always belongs to the core of a game with a nonempty core (balanced) [18].

In this work, we only computed the PreNucleolus since, for more than 16 players, the time and computational effort increased exponentially, and it was not possible to compute. The PreNucleolus only solves the single LP problem, requiring less computational effort.

IV. Case study

The case study that was utilized to support the suggested methodology is explained in this section and can also be found in [19].

Table I shows the different generated scenarios to simulate the LEC management. The first scenario only considers PV generation and a fixed EV control, where EVs charge at the first periods until they reach the needed daily load. Still, the business-as-usual (BAU) and LEC models are proposed in

this scenario. In the first model, agents can only trade with the electricity grid when there is an overproduction or an overconsumption. The second model corresponds to forming a LEC, where agents can trade energy inside the community. In scenario 2, BES are included, and their operation is optimized, with charge and discharge capabilities.

TABLE I
NUMBER OF SCENARIOS GENERATED

Considered technologies	Scenarios	Models
PV + EV*	Scenario 1	BAU LEC
PV + BES + EV*	Scenario 2	BAU LEC

* EV forecasted demand.

Fig. 1 shows the aggregated load consumption and PV generation for 20 agents in the community for 96 periods. The figure shows an overproduction of PV around period 42 till period 60, where its peak value is around 43.84 kW.

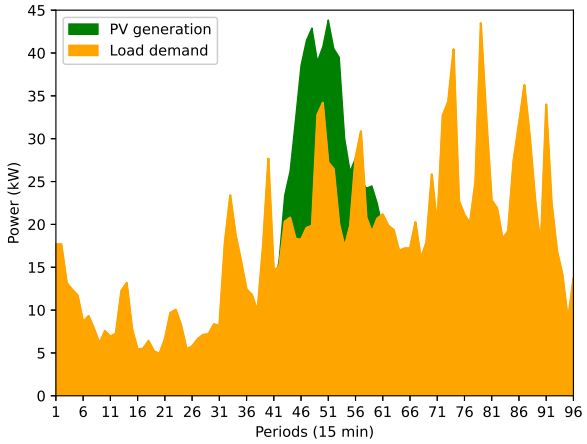


Fig. 1. Aggregated community load consumption and PV generation

Concerning the used price tariffs for buying energy from the grid and selling surplus energy to the grid, Figure 2 shows the feed-in tariff where a constant value of 0.045 €/kWh was considered. A time-of-use retail tariff was used, which is what each agent has to pay to buy energy from the grid, where the minimum and maximum values were 0.1073 €/kWh and 0.2236 €/kWh.

The remaining of the parameter values are described in Table II. In this table, the values for the market prices are described together with the import and export limits for each agent, the forecasted load, PV generation, and EV demand, as well as BES charge and discharge limits and capacity bounds.

Simulations were done on a Windows 11 Pro workstation equipped with a 13th Gen Intel®Core™i9-13900 2.00 GHz CPU and 32 GB of RAM using the Python programming language, with the Gurobi[1] optimization solver for the BES optimization.

[1]https://www.gurobi.com/

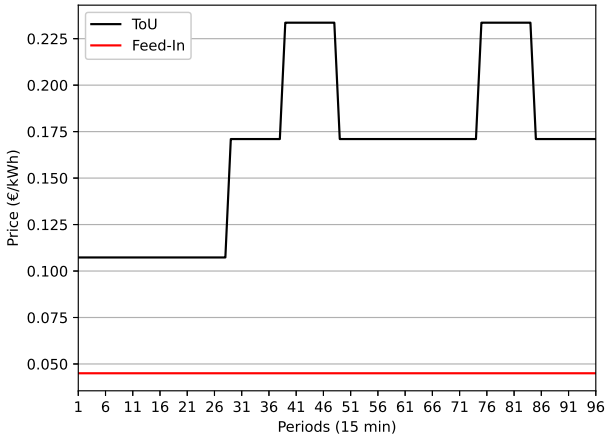


Fig. 2. Feed-in and time-of-use tariffs

TABLE II
PROBLEM PARAMETERS.

Parameter	Description	Value	Units
s_t^{buy}	Grid buy	0.1073-0.2236	€/kWh
s_t^{sell}	Grid sell	0.045	€/kWh
$p_{i,t}^{\text{load}}$	Forecasted load consumption	0.05-7.70	kW
$p_{i,t}^{\text{gen}}$	Forecasted PV generation	0-8.47	kW
im_i	Maximum import	13.8-20.7	kWh
ex_i	Maximum export	13.8-20.7	kWh
b_i^{chMax}	Limit BES charge	2-6.5	kW
b_i^{dchMax}	Limit BES discharge	2-6.5	kW
η_f^{bat}	BES charge/discharge efficiency	0.945-0.97	-
soc_i^{bEnd}	Final BES state-of-charge	3.2-6.45	kWh
soc_i^{minCap}	Minimum BES capacity	1.216-2.451	kWh
soc_i^{maxCap}	Maximum BES capacity	6.4-12.9	kWh
$vh_{i,k,t}^{\text{ch}}$	EV home charge	0.13-11	kW

V. RESULTS

Regarding simulation results, for 20 agents, Table III shows the total costs for each proposed scenario in the BAU and LEC methodologies, as well as the total obtained benefit when the agents form a community to share their energy locally. When considering only PV generation with a prediction of EV demand with no control, the community costs are greater with no transactions between agents. Still, when users form a LEC with trading capabilities, the costs are reduced by 6.19 €. When BES are introduced, the costs reduce by 11.13% in the BAU model and 16.43% in the LEC model compared to only when PV is available. The costs in the community between the BAU and LEC are reduced by 9.29 € in scenario 2. The benefits of the community in both models are the values that need to be distributed among each community agent.

Fig. 3 shows the benefit distribution strategies of the total benefits for each agent in each proposed scenario. In scenario 1 (upper subplot), players 5 and 15 seem to benefit most in the proposed strategies, mainly when SDR pricing is used.

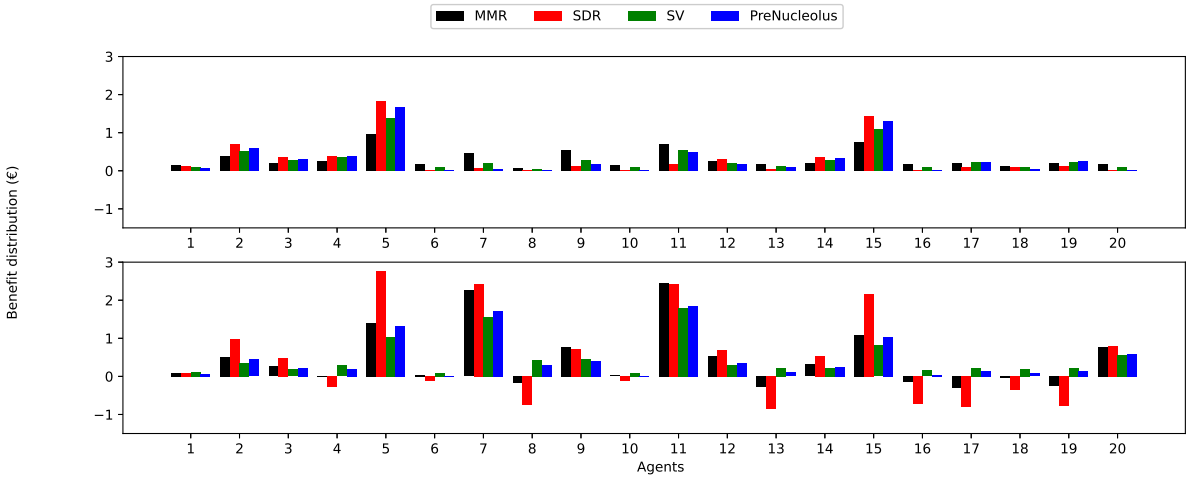


Fig. 3. Benefit distributions according to the proposed mechanisms for scenario 1 (upper) and scenario 2 (lower)

TABLE III
TOTAL SCENARIO COSTS (IN €).

	Scenario 1	Scenario 2	Reduction (%)
BAU	77.57	68.94	11.13%
LEC	71.38	59.65	16.43%
Total Benefits	6.19 (7.98%)	9.29 (13.48%)	-

In the second scenario, negative distributions can be observed for some users considering MMR and SDR strategies. This negative distribution means that users would be better off in these strategies than in the LEC since their energy bill would be greater. Users 5, 7, and 11 receive the largest benefits since they have a large load demand, and their energy bill is expensive outside the community, so they benefit the most when a LEC is formed.

Fig. 4 shows the excesses of a 20-agent game coalition for scenario 1 of each distribution strategy. It is possible to observe that in MMR, many excesses are greater than zero, which means that in some of the coalitions, the players would be better off leaving the community. Also, it is worth noting that this does not occur in PreNucleolus since all excesses are lower than zero, and since it optimizes the excesses, the game is stable.

In comparison, in Fig. 5, the excesses for the second scenario are shown. In this case, for MMR and mostly SDR, there is a lot of dissatisfaction in a large number of coalitions since a lot of the values are greater than 0. In contrast, in SV and PreNucleolus, each coalition is satisfied being in the community, as only a few coalitions would be better off departing from it.

The computational times for each distribution strategy are presented in Tab. IV. A comparison is made between each strategy, where the times of the SV and PreNucleolus increase as the number of agents increase, mainly the PreNucleolus. This strategy, with such massive computational effort, is not very viable for short-term operation and distribution schedules

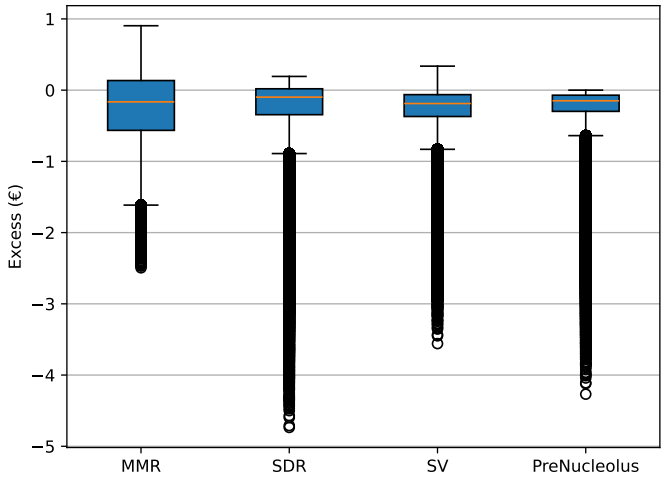


Fig. 4. Coalition excesses for each distribution strategy in scenario 1

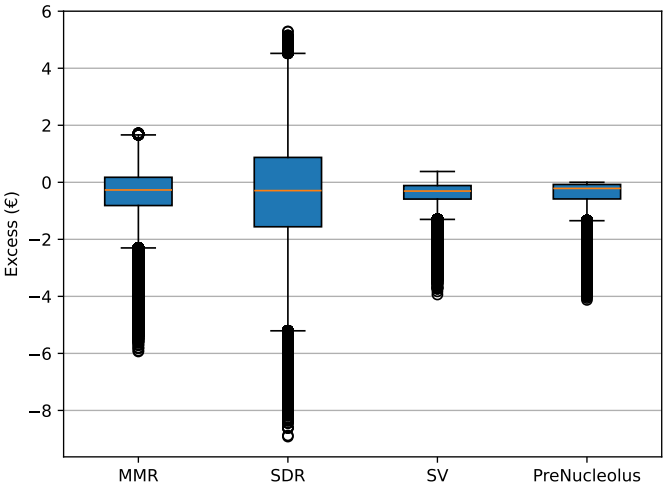


Fig. 5. Coalition excesses for each distribution strategy in scenario 2

in the LEC paradigm.

TABLE IV
TOTAL COMPUTATIONAL TIME FOR EACH STRATEGY (IN SECONDS).

N	4	8	12	16	20
MMR	0.0003	0.0005	0.001	0.001	0.001
SDR	0.0003	0.0004	0.001	0.001	0.001
SV	0.0002	0.0004	0.020	0.31	7.40
PreNucleolus	0.004	0.016	0.26	5.05	37.46

VI. CONCLUSIONS

The proposed work encompassed multiple benefit distribution strategies for LECs based on game-theoretic approaches. Two scenarios were generated, one considering only agents with PV generation to trade and another considering the inclusion of BES. The EV demand was modeled as a prediction value in both scenarios.

The results suggest that the introduction of BES reduced the cost of the users between 11% and 16%. The total benefits are distributed in both scenarios using state-of-the-art approaches such as the MMR, SDR, SV, and PreNucleolus. SV and PreNucleolus, the last two, are referenced as fair approaches since they consider the benefits of each coalition made in the game-theoretic approach. SV can guarantee more fairness from the perspective of the marginal contribution of each player to the coalition and more happiness for the energy community as a collective entity. Still, neither Nucleolus nor Shapley Value can guarantee both fairness and stability simultaneously.

The proposed work can be further extended. The authors plan to implement the proposed methods on a larger scale, e.g., with energy communities with 100 players adopting approximation methods for both stability and fairness issues. Moreover, the authors also plan to implement more realistic approaches to energy communities, including regulation aspects and network constraints as the problem of optimally organizing a set of interested nearby members to form energy communities to improve benefits and contribute to social and environmental issues.

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