HeliosFair: Fair Sharing of Solar Energy Costs in Communities

Diptyaroop Maji[1], Vani Gupta[2], Prashant Shenoy[1], Ramesh K. Sitaraman[1]

[1]University of Massachusetts Amherst, [2]Roger Williams University

Abstract

As solar electricity has become cheaper than the retail electricity price, residential consumers are trying to reduce costs by meeting more demand using solar energy. One way to achieve this is to invest in the solar infrastructure collaboratively. When houses form a coalition, houses with high solar potential or surplus roof capacity can install more panels and share the generated solar energy with others, lowering the total cost. Fair sharing of the resulting cost savings across the houses is crucial to prevent the coalition from breaking. However, estimating the fair share of each house is complex as houses contribute different amounts of generation and demand in the coalition, and rooftop solar generation across houses with similar roof capacities can vary widely. In this paper, we present HeliosFair, a system that minimizes the total electricity costs of a community that shares solar energy and then uses Shapley values to fairly distribute the cost savings thus obtained. Using real-world data, we show that the joint CapEx and OpEx electricity costs of a community sharing solar can be reduced by 12.7% on average (11.3% on average with roof capacity constraints) over houses installing solar energy individually. Our Shapley-value-based approach can fairly distribute these savings across houses based on their contributions towards cost reduction, while commonly used ad hoc approaches are unfair under many scenarios. HeliosFair is also the first work to consider practical constraints such as the difference in solar potential across houses, rooftop capacity and weight of solar panels, making it deployable in practice.

CCS Concepts

• **Theory of computation → Algorithmic game theory**; • **Hardware → Renewable energy**.

Keywords

energy community, cost minimization, fair sharing, Shapley value

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1 Introduction

Solar continues to be a widely adopted source of renewable energy, accounting for nearly 75% of electricity-generating capacity added to the U.S. grid in the first quarter of 2024 [22]. Moreover, solar installation costs have declined by 40% in the last decade. Despite the decline in cost, customer-level efficiencies that further reduce the cost of rooftop solar installations are useful for increasing rooftop solar adoption since there continues to be a pressing need to turn to renewable energy sources due to the escalating climate crisis.

One way residential customers can reduce their costs is by forming a solar energy coalition. In this paper, we propose an approach where coalitions optimally place solar panels in high-generation shared rooftop areas, thereby reducing the total number of panels needed to meet aggregate demand, and then share the savings. Members of a coalition contribute different amounts of generation and consumption. Some members may have rooftops with a large area or a high solar generation potential. Others may have energy demands that need to be met using solar energy. The total demand can be met using solar energy generated by the coalition at the lowest possible cost by placing panels at the highest generation potential locations. Thus, once the cost is reduced, sharing the savings fairly is critical to incentivize customers to stay in the coalition. Savings can be shared in various ways. Approaches like sharing cost savings proportional to demand favour homes with higher demand. Similarly, sharing proportional to solar generation favours homes with higher solar generation. However, both the demand for and the generation of solar energy are necessary for realizing savings. Hence, considering only demand or generation would be unfair and may prevent the houses from forming coalitions. Additionally, solar generation varies even among neighbouring houses with similar roof capacities [14]. Cost-sharing approaches that ignore this variation do not accurately model reality and may be unfair to a house that can provide solar energy at a lower cost by giving it equal savings as another house that provides the same amount of energy at a higher cost. Consequently, a more sophisticated approach is needed that takes a comprehensive view of the diverse contributions and is fair to all coalition members.

Research contributions. In this paper, we use Shapley values to fairly share the total electricity cost of houses in a community that form a coalition and share solar energy to reduce the overall cost. First, we devise an algorithm that realistically models and minimizes the solar panel installation and electricity procurement costs. The algorithm reduces costs by optimally placing panels on high-generation rooftops and allowing other houses to share the generated solar energy for maximum savings. Then, we use Shapley values to estimate the cost of each house by fairly distributing these savings based on their contributions.

Prior works on cooperative cost reduction and fair sharing have used Shapley values or other similar methods [2–6, 10, 15–17, 20, 21]. However, these works only reduce the OpEx costs of purchasing electricity, ignoring the significant CapEx costs of installing panels. Recently, some works have considered the CapEx costs in their cost formulation [1, 11, 19]. However, they ignore the variation in solar generation across nearby houses and even across different panels within a house [14]. In contrast, our work minimizes the cumulative CapEx and OpEx costs while considering solar generation variation and designs a more realistic cost minimization algorithm and savings distribution method. Our specific contributions are:

(1) We develop HeliosFair, a system that formulates solar energy sharing in a community as a cooperative game and fairly divides the savings obtained using a Shapley-value approach. HeliosFair considers real-life factors like diverse solar potentials and roof capacity constraints to build a realistic cost-minimization and fair savings distribution model that is deployable in practice.
(2) We evaluate HeliosFair on a real-world solar generation and electricity consumption dataset comprising 3038 houses and find that sharing solar energy can reduce the joint CapEx and OpEx costs of a community by 12.7% on average (11.3% on average with roof capacity constraints). HeliosFair then divides these savings across the houses fairly based on their contribution using Shapley values. We also provide insights into why ad hoc approaches fail to distribute the savings in a fair manner and how the Shapley value approach results in fair savings distribution with respect to community cost reduction. Intuitively, HeliosFair provides more savings to houses with either more surplus generation or more surplus demand.

2 Background and Problem Statement

In this section, we discuss energy communities, net metering, and Shapley values. We also define our problem statement.

Energy Communities. Our paper focuses on the approach where nearby houses share solar energy across a distributed group of solar arrays. We use the terms *energy community* and *coalition* to mean a group of consumers installing a set of shared solar arrays on their rooftops, and consider the collective rooftop areas that they make available to the coalition as one single logical rooftop. Such coalitions benefit both the coalition members and the environment, as they reduce the electricity costs of members due to shared solar infrastructure and increase the amount of green energy in the grid.

Net Metering. Net metering to the grid is an approach where a consumer with a solar array can feed any excess solar generation (after meeting local demand) to the grid. The credits from feeding such excess solar generation can then be offset against energy consumed from the grid (e.g., at night). Net metering is beneficial as it allows customers to reduce their electricity bills by using the credits. Currently, some regions have started allowing the transfer of net metering credits across customers to incentivize more solar installation and hence, more clean energy generation [18].

Shapley Values. The Shapley value [24] is a fair way to distribute the total payoffs across N players in a coalition playing a cooperative game. For each player, the Shapley value obtains their payoff as a weighted average of the marginal contribution of that player across all possible coalitions (S). Mathematically, player i gets:

$$\phi_i(v) = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N| - |S| - 1)!}{|N|!}(v(S \cup i) - v(S)) \tag{1}$$

As an application, an energy community can use Shapley values to fairly distribute the cost savings obtained by forming a coalition.

Problem Statement. Our problem statement is as follows:

Given a coalition of N houses in a community who cooperatively share their rooftops, we want to minimize the total community cost of solar panel installation and electricity purchase to meet the cumulative demand. Once the cost is minimized, we then want to distribute the savings obtained fairly across the houses, according to their contribution towards this community cost reduction.

3 HeliosFair Design

Houses generate different amounts of solar energy even when geographically proximal due to several factors like panel placement, roof and the panel directions, shading, roof shape, etc. While some houses can generate more solar energy than their electricity demand, others can only meet a fraction of their demand. By forming a coalition, houses can invest together to install more solar panels on houses with surplus capacity and share the generated solar energy, increasing the total demand met by solar and thus decreasing the costs. We also observe from our dataset that many larger houses with more solar panels generate equal or even less than smaller houses with fewer solar panels due to the aforementioned factors. Since panel installation cost is directly proportional to the number of panels, meeting the community's electricity consumption with the fewest solar panels possible minimizes the total cost borne by the community. We define the annual solar electricity generated (in kWh) divided by the amortized annual cost of installing solar panels (in $) as the *solar potential* of a house. Coalitions enable installing more panels on higher potential houses and generate the required amount of solar energy using fewer panels, thus further reducing costs. Since the investment is made together, distributing the cost savings fairly across houses is also important to incentivize houses to form and stay in coalitions.

To that end, we propose HeliosFair, a system to minimize the electricity costs of a community by forming coalitions, and then distribute the savings across houses in the community. We formulate HeliosFair as a cooperative game where houses in a community share their roof spaces and invest together in solar panels to minimize the total electricity cost borne by the community. Once the cost is reduced, HeliosFair then distributes the cost savings obtained due to solar energy sharing fairly, using the Shapley value approach. HeliosFair works on an annual scale and consists of two components — (1) Cost-Minimization Component (CMC), and (2) Fair-Sharing Component (FSC).

3.1 Cost-Minimization Component (CMC)

Given a coalition of houses, CMC minimizes the total cost of installing solar panels (CapEx) and purchasing electricity from the utility (OpEx) to meet any demand not met by solar. It then provides the savings obtained by coalition formation. CMC estimates the costs as follows: **(1) Solar panel installation cost (CapEx):** We consider 400W solar panels costing $3.40 per Watt [9], and amortize this cost equally over the 20-year panel lifespan [12]. **(2) Cost of purchasing electricity from the utility (OpEx).** We consider the average residential electricity rate of 0.22 $/kWh [8] for simplicity. We posit that since we are doing an annual analysis, calculating

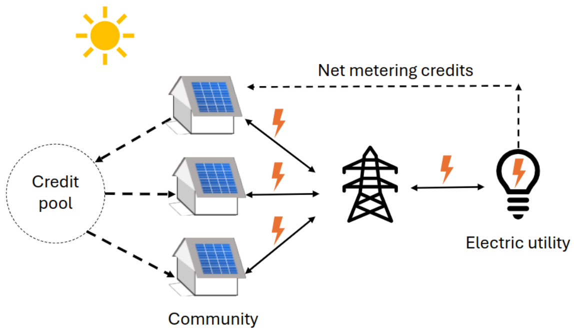


Figure 1: HeliosFair design. Each home also connects to the power grid and is net-metered. The net metering credits are deposited and retrieved from a common pool to offset costs of purchasing electricity from the utility.

the cost using time-of-use prices would give very similar values to the average price when aggregated over a year.

Given a coalition and per-panel generation for each house in the coalition, we allocate a panel if its marginal installation cost is less than the utility's electricity price. This cost is calculated by dividing the solar panel installation cost by the annual electricity generated by that panel, i.e., it is the inverse of its solar potential. We start with the panel having the least marginal cost so that the total number of panels, and hence, the *CapEx*, is minimized. We do this until we run out of roof space, or meet the total annual demand of the coalition, or the marginal cost exceeds the utility price. Any remaining demand is met by purchasing electricity from the utility.

3.2 Fair-Sharing Component (FSC)

Once CMC provides the savings of a coalition (S), FSC distributes it fairly using the Shapley value approach. Intuitively, houses contributing more towards reducing the total cost get more savings.

Value function. Our value function is as follows:

$$v(S) = \left(\sum_{i \epsilon S} C_i\right) - C_S \tag{2}$$

Thus, the value function is the difference between the sum of individual costs borne by the houses if they did not form a coalition ($\sum_{i\epsilon S} C_i$) and the total cost incurred by the houses after they formed the coalition (C_S). Once the values are obtained for all possible coalitions, we get the final distribution using Equation 1. Note that when $|S| = 1$, there is no savings ($C_i = C_S$). Hence, $v(S) = 0$.

3.3 Practical considerations

Our model provides a theoretical framework for cost reduction and fair sharing. However, there are scenarios and constraints that may affect the feasibility of HeliosFair. In this section, we discuss how we handle such cases to make HeliosFair feasible in practice.

Matching OpEx cost with solar generation. Our cost model considers zero OpEx cost if the annual generation matches the annual demand. In reality, solar generation occurs during the day, while electricity demand is continuous. CMC accounts for this by considering that houses get credits via net metering and use those credits to offset the electricity costs when generation is insufficient. However, there are two problems. First, net metering and electricity bills are generated every month. In some months, the total demand may exceed the total generation, and the electricity bill (OpEx) may become greater than zero. This is especially true during the winter when there is less solar generation. Thus, the total cost in practice may not match the cost returned by our algorithm, as credits cannot be backdated. Second, although the houses invest together, they have separate meters. So, only the houses with solar panels installed on their roofs get net-metering credits in practice, while the other houses still have to buy electricity from the grid at retail price.

HeliosFair can be designed in multiple ways to tackle these issues. As an example, we propose using a common credit pool where houses can use surplus net metering credits deposited by other houses to offset the electricity cost. Figure 1 shows how HeliosFair works in practice. Since credit usage cannot be backdated, we assume that the annual cycle starts in the summer so that the credit pool will have enough reserves during the winter. As long as the annual demand matches the annual generation over a year, the community can always meet their demand with solar generation using net metering credits and make the OpEx zero each month.

Rooftop and grid capacity constraints. It may not be practical to install panels till a roof reaches its capacity due to grid constraints like Low Voltage (LV) network constraints or limits set by utilities on how much solar can be exported at one time. It may also be the case that a roof cannot handle the weight of too many solar panels (one panel weighs ~40 lbs [7]). While modelling grid constraints is complex and may require knowledge about the grid topology, limiting the number of panels on the rooftops is one way to simulate all the above cases. In this paper, we simulate such scenarios by limiting the number of panels on any roof to 50. HeliosFair can be extended with minimal changes to incorporate variable rooftop capacity constraints and simulate a more realistic scenario.

Privacy issues. CMC assumes that the electricity consumption data and the electricity bill of each house are public information. Currently, we do not address the privacy and security concerns that may pose. One way to handle these issues is by designing a trusted centralized agent that runs the CMC and FSC for the community so that any private information is not available to others. We keep designing a privacy- and security-aware system for future work.

Handling new panel additions and panel malfunctions. We assume that houses install the maximum number of possible panels at the start to ensure maximum cost reduction. In reality, houses may install panels at different periods. Our system can handle cases like new houses joining the coalition or houses installing panels in different years without any changes. Our algorithm runs annually and calculates the cost share each year depending on the current configuration. There will still be savings if there are not enough panels to meet the total demand, but it will be lower than if there were sufficient panels.

Another issue in practice is that panels may malfunction at any time, affecting cost reduction and distribution, whereas CMC and FSC assume that the panels work properly throughout the year. Since HeliosFair works on an annual scale, we can model panel malfunctions using some known statistical distribution and modify the total annual cost of each subcoalition in the community and then distribute the savings. However, this requires detailed analysis, and we keep this as future work.

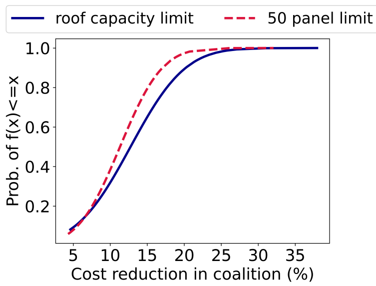
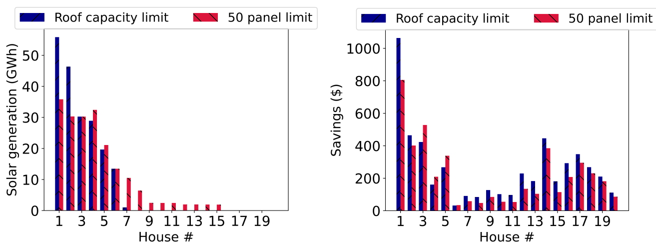
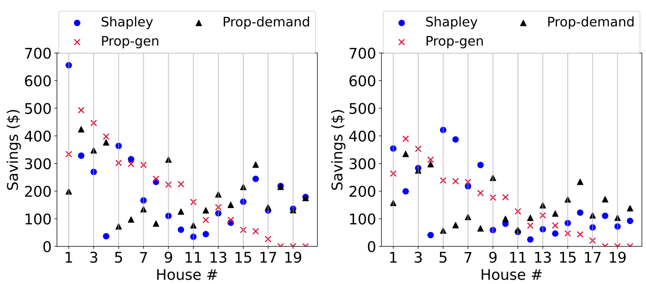


Figure 2: CDF plot showing the range of decrease in cost when communities form coalitions.



(a) Solar generation in coalition. **(b) Savings in coalition.**

Figure 3: Solar generation resulting from CMC and consequent savings distribution using FSC.



(a) No capacity constraints. **(b) With capacity constraints.**

Figure 4: Shapley value approach rewards both surplus solar generations and surplus demand and is fair, while other approaches may not distribute savings appropriately.

Scalability of FSC. FSC currently handles small-sized coalitions since Shapley values have exponential computational time. However, recent efforts [6, 19] have developed algorithms that can closely approximate the exact payoff vector distribution obtained by Shapley values in polynomial time. FSC can incorporate these algorithms to scale to larger coalitions.

4 Experimental Evaluation

We evaluate our approach across 3038 single-family houses in a city in the northeastern part of the US. We use real-world annual solar generation data from Google's Sunroof project [13] and actual electricity consumption data for a year obtained from [23].

4.1 Cost Savings from Coalition Forming

We sorted the 3038 houses geographically based on their latitude and longitude and sequentially picked 20 houses as one community, resulting in 152 communities that can form coalitions.

Figure 2 (blue line) shows a CDF plot of the decrease in cost due to forming coalitions. When aggregated across all the coalitions, the cost decreases by 12.7% on average and up to 37.9%. This equates to saving $516.6k in annual electricity costs in total. Note that grouping neighbouring houses to form a coalition may not be optimal as neighbourhoods with no houses having surplus solar production may exist. Forming coalitions that get the most cost reduction needs more analysis and is not the focus of this paper.

Figure 2 (red line) shows cost reduction under capacity constraints (each roof can install up to 50 panels). All coalitions show a decrease in savings, with coalitions having fewer high-potential houses being affected more. However, there is only a small decrease in savings (from 12.7% to 11.3%) compared to the theoretical case when averaged across all the coalitions. Thus, HeliosFair is deployable in practice.

4.2 Savings Distribution Using Shapley Values

We now show how FSC distributes the savings across the houses in a representative coalition. Figure 3 shows the houses in the coalition in decreasing order of their solar potentials. All houses except house 14 can meet their individual demands using solar energy.

Figure 3a shows the solar energy generated by each house in the grand coalition. Houses with surplus capacity and higher solar potentials generate more. Some houses do not generate any solar energy in the coalition due to their low potential. When we limit the capacity to 50 panels per roof (red bars), panels are placed on more roofs as houses with higher potentials reach their limits.

Figure 3b shows each house's savings distribution using the Shapley value approach with (red) and without (blue) capacity constraints. The savings depend on their contributions towards the total cost reduction across all possible subcoalitions, with houses getting more savings if they contribute more. Houses generating a lot of surplus energy get higher savings. On the other hand, house 14 also gets high savings because it brings in demand that utilizes the solar energy generated by other houses. From our data, we see that house 6 generates a lot of solar energy individually and in coalition. However, it mostly consumes the generated energy itself. Hence, it contributes very little to reducing community costs and gets the least savings.

Under capacity constraints, since house 1 is capped at 50 panels, its contributions towards cost reduction and, subsequently, savings obtained via Shapley values decrease. Most houses get less savings when there are capacity constraints. However, some houses see an increase in savings. In this coalition, house 3 generates the same amount of solar in both cases. Thus, its contribution increases across subcoalitions when the panel count is limited to 50 per house, and hence, it receives more savings.

4.2.1 ***Fairness in Cost Savings Distributions.*** A fair approach should only consider the contribution of a house towards the community cost reduction. Since the cost is reduced either via surplus solar generation or via surplus demand, the approach must reward both appropriately while also considering that even a house with high solar and high demand may contribute little surplus to the community. Also, if two houses generate the same amount of solar energy, the house that can generate at a lower cost should get more savings. To that end, we evaluate the fairness of the Shapley value approach and show why other approaches to distributing the savings are unfair. We consider distributing the savings proportional to electricity consumption (demand) or solar generation in the coalition as our baselines.

Figure 4 shows another coalition in decreasing order of their solar potentials. Houses 1 and 5 contribute a lot of surplus solar, whereas houses 16 and 18 have high surplus demand. House 4 has high generation and demand, but most of its generation meets its demand. Hence, it contributes little to community cost reduction. Figure 4a shows that the Shapley value approach recognizes all these nuances, allocating more savings to houses 1, 5, 16, and 18, and minimal savings to house 4. In contrast, generation-proportional or demand-proportional approaches fail to reward houses fairly with respect to their contributions. Both these approaches provide high savings to house 4 as its generation and demand are high. The demand-proportional approach provides less savings to house 5, although it provides a significant amount of surplus solar. On the other hand, the generation-proportional approach provides no savings to houses 18, 19, and 20, despite their demand contribution.

Under capacity constraints (Figure 4b), house 1 gets reduced savings with HeliosFair since it can now install only 50 panels, while houses 5 and 6 get more savings as they can now contribute more solar generation. The demand-proportional approach ignores capacity constraints since demand remains unchanged. Since it does not consider changes in generation, a house with high demand will still get more savings even if it has no surplus generation due to capacity constraints. The generation-proportional approach recognizes these constraints, but it is skewed towards houses with high generation, even if they use most of it to meet their own demand. Although distributing with respect to the solar potential may seem to be a better metric, since it does not allocate savings to houses with high demand but no roof capacity, it is unfair to them.

Key Takeaways:
(1) HeliosFair distributes the savings based on each house's contribution towards community cost reduction. Houses with more surplus generation get more savings as it helps to meet demand at a lower cost. However, panels are only installed when there is demand. So, houses with high surplus demand also get more benefits, as it enables solar panel installation and subsequent cost reduction.
(2) Houses with high generation or demand may not reduce the community cost if they use most of their generation themselves. Simple distribution approaches that look solely at generation or demand can unfairly provide more savings to these houses than those that contributed more. Additionally, distributing proportionally to demand (resp. generation) does not allocate any savings to houses that contribute only with generation (resp. demand). Shapley value allocates savings proportional to the actual contributions of houses regardless of their generation or consumption, with a house getting more benefits than another house if it generates the same amount of solar at a lower cost, and hence, is fair.

5 Conclusions

In this paper, we developed HeliosFair, a system to fairly distribute the cost savings obtained by houses in an energy community. Using real-world solar generation and electricity consumption data, we showed that the joint CapEx and OpEx electricity costs of the community can be reduced by 12.7% on average (11.3% with capacity constraints) when houses share solar energy. We also showed HeliosFair can fairly distribute these savings across houses based on their contributions towards cost reduction, while other ad hoc approaches may be unfair under many scenarios.

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