Efficient Methods for Approximating the Shapley Value for Asset Sharing in Energy Communities (Encore Abstract)

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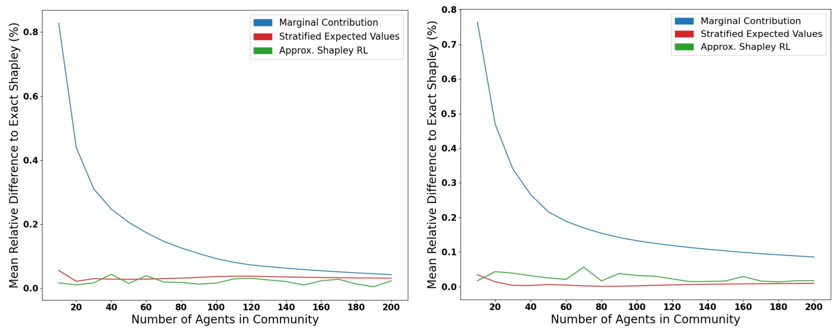
Motivation and Approach As the use of renewable energy increases, there is a shift from a traditional centralised energy generation to a more decentralised energy system where energy prosumers (i.e. consumers with their own generation) satisfy most of their demand locally. This leads to a rise in *energy communities*, where a group of prosumers share the output of a joint energy asset (e.g. community wind turbine, PVs and/or battery storage) and also the residual cost of energy imported from the utility company. Hence, an important challenge is how to *fairly* redistribute the outputs and energy costs among participants in the scheme. Currently, many studies focus on the use of Shapley value, widely considered the "gold standard" for fairness in distribution in a coalitional model. However, the large computational complexity of computing the Shapley value exactly in a setting with many prosumers means its application is often restricted to small community settings with up to $\sim$20 prosumers. Yet, energy communities in real applications and trials can contain 200 participants or more. A number of approximation methods have been previously proposed for energy communities, but there has been no systematic study, to our knowledge, of how well they approximate the Shapley value for larger community sizes.

In our work [2] (and the more extended, follow-up work [1]), we present three main contributions. First, we provide an efficient, deterministic Shapley value approximation method for fair cost redistribution of energy communities, which uses the concept of stratification. For every agent, we create a fictitious demand profile by taking the average demand of the rest of the agents in the community. With this method, it estimates the expected marginal contribution of the prosumer for every stratum using the fictitious demand profile. We call this method *stratified expected values*, and it combines accuracy and efficiency for Shapley value approximation.

Second, we introduce a method to compute the true Shapley value exactly in particular settings by limiting the number of unique demand profiles in the community, which is used as the benchmark to compare the performances of the approximation methods. The Shapley value requires to compute the marginal value for every possible subcoalition in the community, taking an exponential number of steps to the community size. However, by grouping the prosumers into a small number of classes such that prosumers in the same class have the same demand profile, the number of unique subcoalition can significantly be reduced.



(a) Three classes (b) Four Classes

Fig. 1: Approximation performances of redistribution methods.

This method allows to compute the exact Shapley value efficiently even for large communities, which is then used as a benchmark for the approximation methods.

Third, we implement and demonstrate the redistribution methods in case studies with realistically-sized energy communities in the UK sharing a wind turbine and battery. In [2], the demand data is drawn from the Thames Valley Vision project[4]. From the demand data, three unique demand profiles are created, and the energy communities of 10 to 200 prosumers are formed from the three classes. Furthermore, additional experiments are performed in [1], where demand data from the Low Carbon London project[5] is used to create energy communities with four unique demand profiles. The true Shapley values are used as the benchmark to compare the approximation performances of three cost redistribution methods. The first method used is the marginal contribution method [3, 4], which is a simple and efficient deterministic approximation method. Second is the newly proposed stratified expected values method. Third is the adaptive sampling method based on reinforcement learning [5], which is the state-of-the-art, non-deterministic method.

Results Figure 1 presents two of the results from our studies, which are the approximation errors (in percentage) of the three redistribution methods for different community sizes. Figure 1a shows the performances of the methods where the communities are made up of three unique demand profiles, whereas Figure 1b is for four classes. The results show that all three methods approximated the Shapley value well for large communities. In particular, the newly proposed stratified expected values and the state-of-the-art adaptive sampling method perform extremely close to true Shapley values in almost all scenarios studied. Furthermore, stratified expected values performed comparatively with the adaptive sampling method and outperformed in many scenarios while having a much smaller computational cost.

[4] `https://ukerc.rl.ac.uk/DC/cgi-bin/edc_search.pl?WantComp=147`

[5] `https://www.kaggle.com/datasets/jeanmidev/smart-meters-in-london`

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