Cooperative Energy Exchange for the Efficient Use of Energy and Resources in Remote Communities

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ABSTRACT

Energy poverty at the household level is a serious hindrance to economic and social development, especially in off-grid, remote villages in the developing world. Some initiatives have sought to provide these households with resources such as renewable generation units and electric batteries to enable access to electricity. At present, these resources are operated in isolation, fulfilling individual home needs, which results in an inefficient and costly use of resources, especially in the case of electric batteries which are expensive and have a limited number of charging cycles. To address this problem, we investigate the exchange of energy between homes in a community to reduce the overall battery usage, thus prolonging the life of batteries. We take an agent-based approach to this problem and show that agents (acting on the behalf of households) can coordinate and regulate the exchange of energy between homes which leads to two surpluses: reduction in the overall battery usage and reduction in the energy losses. To ensure a fair distribution of these surpluses among agents, we model this problem as a coalitional game where each agent's contribution to both surpluses is computed using the Shapley value. Using real world data, we empirically evaluate our solution to show that energy exchange (i) can reduce the need for battery charging (by close to 65%) in a community and (ii) can improve the efficient use of energy (by up to 80% under certain conditions). In addition, we show how approximated Shapley values can be used to enable energy exchange in large communities.

Categories and Subject Descriptors

I.2.11 [**Computing Methodologies**]: Artificial Intelligence, Distributed Artificial Intelligence.

General Terms

Agents, Multi-Agent Systems.

Keywords

Energy Exchange, Storage, Battery, Off-grid, Cooperative Exchange.

1. INTRODUCTION

Energy poverty at the household level is defined as the lack of access to electricity and reliance on the traditional use of biomass for cooking, and is a serious hindrance to economic and social development [10, p.237]. It is estimated that 1.4 billion people live without access to electricity and almost 2.7 billion people rely on biomass for cooking [10, p.239], a majority of whom live in small communities scattered over vast areas of land (mostly in the Sub-Saharan Africa and the developing Asia). Access to electricity is a serious issue as a number of socio-economic factors, from health to education, rely heavily on electricity [16, p.14]. Recent initiatives have sought to provide these remote communities with off-grid renewable microgeneration infrastructure such as solar panels, and electric batteries.[1] At present, these resources (i.e. microgeneration and storage) are operated in isolation for individual home needs and we envision that the interconnection and autonomous coordination of such resources could not only result in the efficient of use of these resource and energy, but can also help cut down the infrastructure and maintenance cost.

As a first step towards this vision, we explore the possibility of energy exchange between homes to reduce the overall usage of electric batteries in a community. Electric batteries are expensive (costing as high as 500 USD/kWh) along with a limited number of charging cycles (3000 to 5000), requiring them to be replaced more often, compared to other components in an off-grid system. We believe that enabling households to exchange energy can help them reduce the overall need for energy storage, thus prolonging the life of their batteries and reducing the need for frequent replacements. However, enabling energy exchange between homes poses many issues that come from the very nature of these communities and realities of life in developing countries, e.g., absence of banking/payment systems, low processing power at hand and individual and communal power needs. Taking these issues into account, we need an autonomous and tractable energy exchange solution, that can operate without financial payments between homes, and benefits all participants.

Against this background, we approach this problem by modeling each home's resources as being controlled by an intelligent agent that acts on the behalf of a household to maximise its utility. We consider the homes to be interconnected, forming a multiagent system where agents can interact to exchange energy. Given that the agents are self-interested, we propose an energy exchange solution where it is individually rational for an agent to participate. Our solution then identifies the mutual benefits of the exchange, in terms of the overall reduction in battery usage and improvement in the energy efficiency, and using the Shapley value computes the fair

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[1]See the Rural Solar Homes in India (www.tatabpsolar.com), the Solar Homes program in Bangladesh (www.gshakti.org), the Solar Village program in Ethiopia (www.solarsenegal.com) and the Folovhodwe Village Project in South Africa (http://www.hedon.info).

share for each agent's participation. Our empirical evaluation of this solutions show that energy exchange can help reduce the need for storage while improving energy efficiency. In more detail, this work advances the state-of-the-art in the following ways:

1. We present a novel Shapley value-based cooperative solution that can be used for energy exchange in remote communities.
2. We show that it is individually rational for agents to participate in our energy exchange solution.
3. We empirically evaluate our solution and show that in this instance:
    - Overall battery usage can be reduced by nearly 65% while maintaining the same utilities that agents get with no exchange.
    - Energy efficiency can be increased by up to 80% depending on the overall battery usage and efficiency.
    - Energy exchange in larger communities is possible by approximating the Shapley values.
    - Exchange becomes more useful as batteries become less efficient with usage over time.

The rest of the paper is structured as follows. We discuss the related work in Section 2. We present our model of homes and community in Section 3, followed by a discussion on coalition formation, the characteristic functions, and the Shapley value calculation. We then empirically evaluate our solution in Section 4 and discuss the results. Finally, Section 5 concludes.

2. RELATED WORK

The idea of energy exchange is not new. There are several real world examples where energy exchange is used to improve energy management between countries (e.g., Finland and Sweden [14]) and between cities (e.g., Delhi and Madhya Pradesh, India). Indeed, exchange of energy has already been shown to result in efficient use of energy and cost savings in utility companies [6, 14]. In this context, Ruusunen et al. [15] considered a group of utility companies, each owning a generator, connected together to form a *power pool*. The cost of energy generation was different for each company and varied over the course of a day, allowing energy exchange to be beneficial to all. In their solution, energy generation and consumption is monitored by the *pool operator* who audits the cost and utility functions of the participants and distributes the cost savings among them. They show that energy exchange results in the efficient use of electricity. However, their approach is not applicable in our case for three reasons. First, they only consider controllable microgeneration (diesel generators) which can be turned on/off on demand, unlike in our setting where microgeneration can be uncontrollable (solar panels or wind turbines are examples). Second, their analysis does not consider the possibility to store energy. Third, their solution depends on monetary payments which renders it useless when payments are not feasible.

In addition, Alam et. al [1] presented a negotiation protocol to facilitate bi-lateral negotiation between two smart homes. This protocol places restrictions on the type and number of offers that homes can make to each other. The negotiation is dependent on the amount of exchange and does not assume side payments. Under certain circumstances, they show that this protocol results in a dominant-strategy equilibrium and that energy exchange between homes can help reduce the need for energy storage in homes by close to 40%. However, their negotiation protocol is bi-lateral and only applicable in two-home settings, thus is not scalable for a community.

In turn, ideas from cooperative game theory have been used in the energy domain for more than a decade [18]. More recently, [4, 13] looked at the advantages of coordinating distributed energy resources (DERs) and showed that their coordination leads to more efficient use of energy. This improvement is measured in terms of monetary payments and they present payment mechanisms for fair division among agents. However, their focus is on coordinating renewable generation only and energy storage is not considered in their work. In contrast, we investigate the coordination of microgeneration resources and storage devices to reduce battery usage and improve energy efficiency. This idea, to the best of our knowledge, has remained unexplored so far.

3. THE ENERGY EXCHANGE PROBLEM

The problem of energy exchange can be viewed at two levels; individual homes and community. We first present a model of an individual home and describe the underlying components (e.g., generation and battery) along with their relationship (e.g. physical constraints) and the utility function. We then describe connecting these homes together to form a community along with how to reduce the overall battery charging. Finally, we present a coalitional model of this community and discuss the characteristic functions along with the calculation and approximation of the Shapley values.

3.1 Model of an Individual Home

In this section, we provide a model of an individual home in a community which is similar to the home models presented in [1, 17]. We assume that each home has a renewable generation unit, some loads and a battery to store electricity. Specifically, let a be an agent representing a home, with a *generation capability* $\boldsymbol{k} = (k_1, ..., k_t) \in \mathbb{R}^t_{\geq 0}$ representing the energy it can generate over $\boldsymbol{t} = (1, ..., t) \in \mathbb{N}^t$ time periods and a *load* $\boldsymbol{h} = (h_1, ..., h_t) \in \mathbb{R}^t_{\geq 0}$ representing its loads requirements. The battery is characterised by four parameters: (i) a maximum storage capacity, $s \in \mathbb{R}_{\geq 0}$, (ii) a maximum charging rate, $c_{max} \in \mathbb{R}_{\geq 0}$, (iii) a maximum discharging rate, $d_{max} \in \mathbb{R}_{\geq 0}$, and (iv) an efficiency $e \in \mathbb{R}_{\geq 0}$. The efficiency describes the loss of energy when the battery is charged. We describe the dynamic state of the battery by: the energy flow into the battery (charge) $\boldsymbol{c} = (c_1, ..., c_t) \in \mathbb{R}^t_{\geq 0}$, the flow going out (discharge) $\boldsymbol{d} = (d_1, ..., d_t) \in \mathbb{R}^t_{\geq 0}$ and the amount of charge stored in battery at any given time $\boldsymbol{q} = (q_1, ..., q_t) \in \mathbb{R}^t_{\geq 0}$.

The generation capability $\boldsymbol{k}$ denotes the energy that *can* be generated, however, an agent may reduce its generation if the energy to be generated can neither be used immediately nor stored due to the limited battery flow or capacity. To capture this possibility, we denote the *generation*, $\boldsymbol{g} = (g_1, ..., g_t) \in \mathbb{R}^t_{\geq 0}$, as the actual energy generated and *wasted energy*, $\boldsymbol{w} = (w_1, ..., w_t) \in \mathbb{R}^t_{\geq 0}$, as the energy that was not generated or *wasted*. Hence, $\boldsymbol{k} = \boldsymbol{g} + \boldsymbol{w}$.

Using the battery, an agent can compute an *energy allocation*, $\boldsymbol{p} = (p_1, ..., p_t) \in \mathbb{R}^t_{\geq 0}$, allocating the generated energy $\boldsymbol{g}$ to loads $\boldsymbol{h}$. The utility of agent a at time i is the ratio of load p_i that is powered at time i, to the total load required (h_i) at time i. The overall utility u_a is the sum of these ratios, given by:

$$u_a = \sum_{i=1}^{t} \frac{p_i}{h_i} \tag{1}$$

Thus, the goal of an agent is to power as much of its load as possible to maximise its utility. The battery is useful here as it gives the agent flexibility in deciding when to store and when to use energy and thus, it enables the agent to find an optimal energy allocation,

$\boldsymbol{p^*}$, given by:

$$\boldsymbol{p^*} = \underset{\boldsymbol{p}}{\operatorname{argmax}} \sum_{i=1}^{t} \left(\frac{p_i}{h_i}\right) \quad \forall\ i \in \boldsymbol{t}$$

We assume that an agent prefers the use of its battery only as much as needed to maximise its utility. To reflect this preference, we include a very small penalty, x, to the above objective function:[2]

$$\boldsymbol{p^*} = \underset{\boldsymbol{p}}{\operatorname{argmax}} \sum_{i=1}^{t} \left(\frac{p_i}{h_i}\right) - x\left(\sum_{i=1}^{t} c_i\right) \quad \forall\ i \in \boldsymbol{t} \qquad (2)$$

This can be transformed to a linear programming model with the following constraints:

Constraint 1: At any given time i, the allocated power $p_i \in \boldsymbol{p}$ depends on the generated power g_i, battery charging flow c_i and discharging flow d_i:

$$p_i = g_i - c_i + d_i \qquad (o_1)$$

Constraint 2: The current battery state q_i depends on the last battery state $q_{(i-1)}$, charge $c_{(i-1)}$ and discharge $d_{(i-1)}$. The charge flow $c_i \in \boldsymbol{c}$ is subjected to the battery efficiency e. Also, the first state of the battery q_1 must equal the last battery state of the battery q_t to ensure there is no net change of battery charge over the day so that the utility remains dependent only on the energy generated in t time periods:

$$q_i = \begin{cases} q_{(i-1)} + e \times c_{(i-1)} - d_{(i-1)} & if\ i > 1 \\ q_t + e \times c_t - d_t & if\ i = 1 \end{cases} \qquad (o_2)$$

Constraint 3: Allocated power p_i must not exceed load h_i:

$$p_i \le h_i \quad \forall\, p_i \in \boldsymbol{p},\ h_i \in \boldsymbol{h} \qquad (o_3)$$

Constraint 4: The battery state q_i must not exceed the maximum capacity s. Also, the battery state cannot be negative, i.e., energy must be stored before it is drawn:

$$0 \le q_i \le s \quad \forall\, q_i \in \boldsymbol{q} \qquad (o_4)$$

Constraint 5: At any time period i, the battery charge flow c_i must not exceed the maximum charge limit c_{max}. Also, the charge flow is always positive:

$$0 \le c_i \le c_{max} \quad \forall\, c_i \in \boldsymbol{c} \qquad (o_5)$$

Constraint 6: At any time period i, the battery discharge flow d_i must not exceed the maximum discharge limit d_{max}. Also, the discharge flow is always positive:

$$0 \le d_i \le d_{max} \quad \forall\, d_i \in \boldsymbol{d} \qquad (o_6)$$

Constraint 7: Wasted energy w_i is always positive and cannot exceed the energy k_i that can be generated at time i:

$$0 < w_i < k_i \quad \forall\, w_i \in \boldsymbol{w},\ k_i \in \boldsymbol{k} \qquad (o_7)$$

Constraint 8: Battery efficiency must be between 0 to 1 (i.e., 0% to 100%).

$$0 \le e \le 1 \qquad (o_8)$$

Now, an agent can compute an allocation $\boldsymbol{p^*}$ which maximises its utility via Equation 2 and constraints $\{o_1, ..., o_9\}$. Here, we are also interested to know the battery charging needed for this optimal allocation $\boldsymbol{p^*}$ and, with a slight abuse of notation, we will use $\boldsymbol{c}$ to denote the battery charging used to get the maximum utility.

[2]In our experiments, we have $x = 0.001$ to ensure an agent will always will prefer the use of battery over its load.

[3]For example, an electric wire allows up to a certain electricity flow. Also, we neglect the electrical resistance on this link.

[4]Although a widely-used assumption in cooperative games, this may well be the case in a small and close-knit community.

3.2 A Coalitional Model of Community

In this section, we first describe how homes can be connected together, given the model in Section 3.1, to form a community. We then transform this community model to a coalitional one.

Connecting Homes Together

A community can be perceived as a collection of connected agents. Connecting any agent to a community requires a physical link flow in between and the dynamics of this physical link can be captured via the electricity flow on the link. Let $\boldsymbol{l} = (l_1, ..., l_t) \in \mathbb{R}^t$ describe the total flow on the physical link for an agent. Now, at any given time, the power available to the connected agent includes the flow on this link (in short *link flow*) at this time. We can modify our constraint o_1 to capture this:

Constraint 9: At any given time i, the allocated power $p_i \in \boldsymbol{p}$ depends on the generated power g_i, battery charging flow c_i, discharging flow d_i and link flow l_i.

$$p_i = g_i - c_i + d_i + l_i \qquad (o_9)$$

Also, we assume that the flow on the link is constrained by its physical properties:[3]

Constraint 10: At any time period i, the link flow l_i must not exceed the maximum link flow allowed on the physical link l_{max}.

$$-l_{max} \le l_i \le l_{max} \quad \forall\, l_i \in \boldsymbol{l} \qquad (o_{10})$$

Coalition Formation

Now given this community of connected agents, we can use cooperative game theory to perceive this community as the *grand* coalition, in its entirety, and where the generation, consumption and storage of agents is common knowledge.[4] Agents in the community are declared self-interested in the sense that they will only exchange energy if it benefits them (i.e., it must be individually rational).

Energy exchange has many potential benefits (e.g., maximising social welfare and managing uncertainty in generation) but we are specifically interested to see if it can help reduce the use of electric batteries as this may reduce the maintenance cost. The reduction in *storage usage*, in our case, equates to reduction in *battery charging*. As discussed in Section 1, the reduction in storage usage has two advantages. First, since a battery has a limited number of charge cycles, reduction in its usage prolongs its life.[5] Second, the less energy stored, the less energy is lost due to the battery inefficiency. Given this, our objective is to minimise the overall battery charging in a community. Now, let N be the set of agents in a community and $n = |N|$. Let $\boldsymbol{c_j} = (c_{(j,1)}, ..., c_{(j,t)})$ define the battery charging needed for the optimal allocation of energy (as detailed in Section 3.1) for agent j when it is not connected. Similarly, let $\boldsymbol{\hat{c}_j} = (\hat{c}_{(j,1)}, ..., \hat{c}_{(j,t)})$ define the battery charging of j when it is connected. In addition, let $\boldsymbol{C^{com}}$ be the matrix of all charging of all agents in the community so that:

$$\boldsymbol{C^{com}} = \begin{bmatrix} \hat{c}_{(j,1)} & \cdots & \hat{c}_{(j,t)} \\ \vdots & \vdots & \vdots \\ \hat{c}_{(n,1)} & \cdots & \hat{c}_{(n,t)} \end{bmatrix}$$

where each row $\boldsymbol{c_j}$ represents the battery charging of agent j over t time periods. Given this, the objective of the community optimisation is to find the minimal battery charging for each agent i.e.,

[5]In Lithium-based batteries, one life cycle means a full charge of the battery even when the charging is discrete.

$\boldsymbol{C^{com*}}$ as the following:

$$\boldsymbol{C^{com*}} = \underset{\boldsymbol{C^{com}}}{\text{argmin}} \sum_{j=1}^{n} \left(\sum_{i=1}^{t} \hat{c}_{(j,i)} \right) \quad \forall\ j \in \boldsymbol{N} \quad \forall\ i \in \boldsymbol{t} \tag{3}$$

Now, $\boldsymbol{C^{com*}}$ contains the minimum battery charging for each agent in the community. We assume that the agents are self-interested so to make it individually rational for them to participate in energy exchange, we include the following two constraints:

Constraint 11: Let u_j is the utility that agent j gets when it is disconnected and $\hat{u}_j$ is the utility while connected. Then:

$$u_j = \hat{u}_j \quad \forall\, j \in \boldsymbol{N} \tag{o_{11}}$$

Constraint 12: Agents are also guaranteed that their battery usage will not increase. Thus, for any agent j:

$$\sum_{i=1}^{t} c_{(j,i)} \leq \sum_{i=1}^{t} \hat{c}_{(j,i)} \quad \forall\, i \in \boldsymbol{t} \tag{o_{12}}$$

Now, given Equation 3 and constraints $(o_2, ..., o_{12})$ we can find the minimum storage requirements of the community. However, a by-product of reduction in storage is energy saving. This energy saving comes from two sources, either from the inability of an agent to store the generated energy due to its limited battery capacity or limited charging/discharging rate (i.e., *wasted energy* $\boldsymbol{w}$ in Section 3.1), or from the energy storage loss due to the battery inefficiency (e in Section 3.1). In particular, we would like to know how much overall energy is saved by using exchange. So if, $\boldsymbol{l_j} = (l_{(j,1)}, ..., l_{(j,t)})$ defines the link flow for agent j then let $\boldsymbol{L^{com}}$ represents all link flows in the community of *n* as follows:

$$\boldsymbol{L^{com}} = \begin{bmatrix} l_{(j,1)} & \dots & l_{(j,t)} \\ \vdots & \vdots & \vdots \\ l_{(n,1)} & \dots & l_{(n,t)} \end{bmatrix}$$

where each row $\boldsymbol{l_j}$ represents the link flow of an agent j over $\boldsymbol{t}$ time periods. To measure this *saved* energy, we introduce $\boldsymbol{l^{saved}} = (l_1, ..., l_t)$ in our model as follows:

Constraint 13: Sum of link flows of all agent at time period *i* equals the saved energy at i.

$$\sum_{j=1}^{n} l_{(j,i)} + l_i^{saved} = 0 \quad \forall\, i \in \boldsymbol{t} \quad \forall\, j \in \boldsymbol{N} \tag{o_{13}}$$

Constraint 14: $\boldsymbol{l^{saved}}$ is always positive.

$$l_i^{saved} \geq 0 \quad \forall\, i \in \boldsymbol{t} \tag{o_{14}}$$

Note, at any given time period i, some agents will have $l_i > 0$, which means they have an outward flow on their physical link, $l_i < 0$ meaning inward flow, or $l_i = 0$ which means no flow for this time period. The difference (between these outward and inward flows) is the saved energy l_i^{saved} in the community at time period i. Here, we would like to stress that the objective of coalition formation is to minimise the battery charging and $\boldsymbol{l^{saved}}$ is a just by-product of this optimisation. Now, given that we can compute the minimum battery charging required for a coalition and the energy saved in that coalition, we now describe a function that, given any coalition, gives us a measure of its importance.

3.3 The Characteristic Functions

In cooperative game theory, a characteristic function v is a function such that $v : 2^N \rightarrow \mathbb{R}$ and $v(\emptyset) = 0$ for a finite set of agents N. In this sense, a characteristic function shows the *worth* or *value* of a given coalition. In our case, agents form a coalition to reduce their battery charging, so we define the worth of a coalition in terms of the total battery charging. We already know that Equation 3 computes the minimum battery charging for a community, therefore, in order to know the overall battery charging of a coalition, we define a characteristic function, v_c, as follows:

$$v_c = \sum_{j=1}^{n} \left(\sum_{i=1}^{t} C_{(j,i)}^{com*} \right) \quad j \in \boldsymbol{N} \quad i \in \boldsymbol{t} \tag{4}$$

where, v_c is the sum of the matrix $\boldsymbol{C^{com*}}$ and shows the total amount of battery charging required in the community. Now, Equation 4 can map any coalition to a number which is the minimum battery charging required in that coalition.

As discussed earlier, a by-product of the reduction in battery charging is energy saving (i.e., $\boldsymbol{l^{saved}}$). To know the worth of a coalition in terms of energy saving, we can define another characteristic function,[6] v_e, in a similar fashion to v_c:

$$v_e = \sum_{i=1}^{t} l_i^{saved} \quad i \in \boldsymbol{t} \tag{5}$$

where v_e is the sum of the vector $\boldsymbol{l^{saved}}$, and shows the overall saved energy in a community.

We make two notes here. First, the battery charging and saved energy for an empty coalition is zero (i.e., $v_c(\emptyset) = 0$, $v_e(\emptyset) = 0$). Second, the input arguments for both Equation 4 and Equation 5 are variables that are the result of optimising Equation 3. Thus, to know both values for a given coalition, we just need to solve Equation 3 to find the values of $\boldsymbol{C^{com*}}$ and $\boldsymbol{l^{saved}}$.

Now, We can know the worth of a coalition which brings up the fundamental question of how to divide it among agents, which we discuss next.

3.4 Fair Division:

For any given coalition, we have two surpluses; battery charging and saved energy, each a transferable utility among agents. From an agent's point of view, it prefers less of the first part (battery charging) and more of the second (saved energy), and given that each agent is self-interested, conflict is natural. The Shapley value is the most widely used solution concept, in coalition formation theory, that deals with dividing the surplus among self-interested agents in a coalition. For a given coalition game (N, v), the Shapley value of agent i is given by:

$$\phi_i(N, v) = \sum_{S \subseteq N \setminus (i)} \frac{|S|!(|N| - |S| - 1)!}{N!} \left[v(S \cup i) - v(S) \right] \tag{6}$$

where ϕ_i is the Shapley value of agent i, N is the set of all agents, v is the characteristic function and S is a subset of N. Note that, the

[6]Note, we could assign weights to map both charging and energy values of a coalition to a single value, say $x \in \mathbb{R}$, to denote the *worth* of a coalition with one value. However, this involves assumptions over weights (i.e., essentially assuming how each agent prefers their charging over their utility) which we avoid by keeping the characteristic functions separated. Also, two characteristic functions make it easier to understand what each agent contributes separately to the overall charging and to overall energy saving, which in turn, makes it easier to give it a fair share in both surpluses.

last part of Equation 6 $[v(S \cup i) - v(S)]$ is known as the *marginal contribution*, of agent i to a coalition S, the difference that an agent makes to the value of a given coalition.

It is obvious that by substituting v_c for v, we can compute the Shapley value for battery charging for an agent, which is what this agent *contributes* on average to the total battery charging requirements of a community. Similarly, substituting v_e will compute the Shapley value for energy saving for an agent, that this agent *contributes* on average to the total energy saving of a community. We call these Shapley values as (i) *charging Shapley value* and (ii) *energy Shapley value*. We now discuss the computational aspects of computing these Shapley values.

3.5 Approximating the Shapley Values

The Shapley value is known to be computationally complex ($2^n \times 2 \times \mathcal{O}(v)$, where $\mathcal{O}(v)$ is the complexity of the characteristic function). Since both characteristic functions are dependent on Equation 3, $\mathcal{O}(v)$ is the complexity of solving a Linear Program (LP). Although, the LP formulation of Equation 3 makes it easy to compute the marginal contribution and scales up with the number of agents (6 seconds for 100 agents), computing the Shapley value for an agent becomes very challenging as we need to know the marginal contribution of that agent to every subset of a given coalition. Therefore, the sheer number of combinations as the number of agents increases, makes exhaustive search impossible (e.g., computing the Shapley values for 16 agents take 21 hours in our case). Some studies focused on this class of problems suggest the use of sampling methods to approximate Shapley value. In particular, Castro et. al. [2] have presented their *ApproShapley* algorithm for the polynomial-time calculation of Shapley value based on sampling. We choose their sampling algorithm for two reasons. First, the complexity of their algorithm is polynomial (not considering the complexity of the characteristic function, which is polynomial in our case). Second, they provide a bound on the approximation of the Shapley value. Also, they have shown their algorithm to be applicable and useful in many coalitional problems (e.g., voting and airport games) which share some similarity with our problem.

The number of samples needed to approximate the Shapley value depends on three factors (i) the error (bound) of the approximation, (ii) an upper bound on the variance of the marginal contributions (iii) and the failure probability of this bound.[7] *ApproShapley* requires the samples from permutations (i.e., $N!$ if N is the set of agents) but we save on the computational time by storing each evaluation of the characteristic function to make sure that the unique coalition corresponding to any permutation is evaluated only once.

This concludes our theoretical part of discussion. In the next section, we set-up an experiment to evaluate our solution based on real world data. This will demonstrate the applicability and advantages of our idea of energy exchange in communities.

4. EMPIRICAL EVALUATION

In this section, we first describe the origin and collection of our data that we use to evaluate our model under general and specific settings. We then discuss the results of our evaluation and demonstrate the usefulness of exchange in communities. In particular, we show how exchange can be useful in different scenarios (inspired by the ground-realities in remote communities) by varying different parameters.

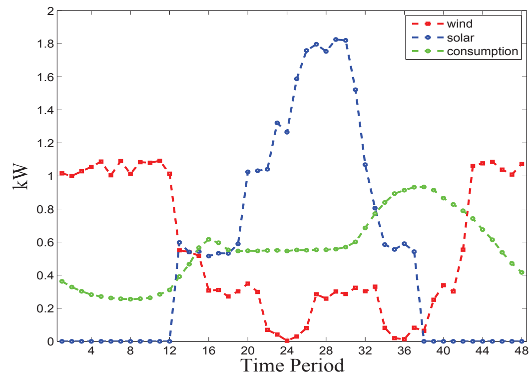


Figure 1: Mean values for a day - generation from solar panel, wind turbine and consumption from low-income UK homes.

4.1 Experimental Setup

We begin by considering a community of agents where each agent has a microgeneration unit, some load and storage as follows:

Renewable Generation: Each agent has a microgeneration unit, either a 1.5kW wind turbine or a 1.75kW solar panel with equal probability. The generation data for the wind turbine comes from a wind farm near Lugo, Northwest Spain[8] while the output of a solar panel is estimated to be directly proportional to the daily radiance for the same region[9]. We use data for July 2011, estimate the average wind and solar generation for a day and scale it to match the output of a 1.5kW wind turbine and a 1.75kW solar panel. Figure 1 shows the scaled generation data for a day. The actual generation for each agent comes from a distribution over the generation profile. More specifically, we model generation in each time unit as an independent Gaussian distribution (with scaled value as the mean and the variance within 10% of it).

Consumption: Load requirements of homes in the remote communities are more challenging as, at present, no such data is readily available. Also, as the demand establishes, the load requirements will naturally increase. To overcome this, we use load data, recorded and provided by a UK electric company in low-income homes equipped with smart meters. Figure 1 shows the mean values for a day, in comparison with the generation data.

Storage: As discussed in Section 3.1, we characterise a battery with 4 attributes, maximum capacity (s), maximum charging rate (c), maximum discharging rate (d) and efficiency (e). In this case, we have considered each agent with one the following batteries[10] with equal probability.

- B1 ($s = 10$kWh, $c = 5$kW, $d = 5$kW and $e = 90\%$)
- B2 ($s = 8$kWh , $c = 4$kW, $d = 4$kW and $e = 90\%$)
- B3 ($s = 6$kWh , $c = 3$kW, $d = 3$kW and $e = 90\%$)

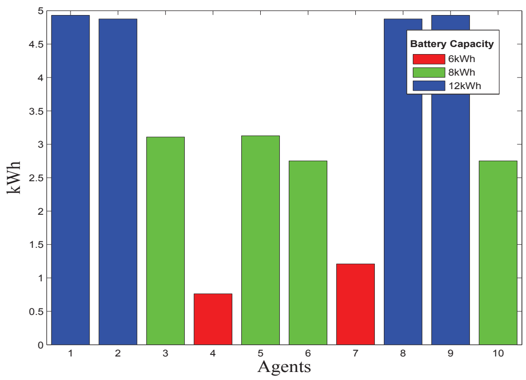
Number of Agents: We initially run our experiments for a community of 10 agents to be able to compute the exact Shapley values and to discuss the comparative variation (and its causes) in the Shapley values of agents. We then consider a community of 100

[7]We set these to $(1.5, 2, 0.05)$ respectively, for the approximation to be correct within ± 1.5 of the actual Shapley values, 95% of times. Thus, there is a 5% chance of an agent's Shapley value being off by more than 1.5. *ApproShapley* needed 112 samples per agent to ensure these requirements in our case. See [2] for a detailed discussion of *ApproShapley* and these parameters.

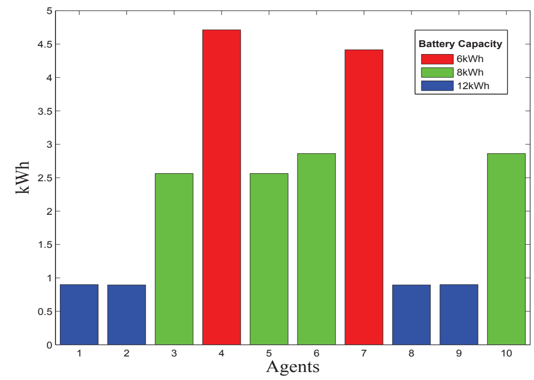
[8]Available at www.sotaventogalicia.com

[9]Available at www.re.jrc.ec.europa.eu/pvgis/apps/radday.php

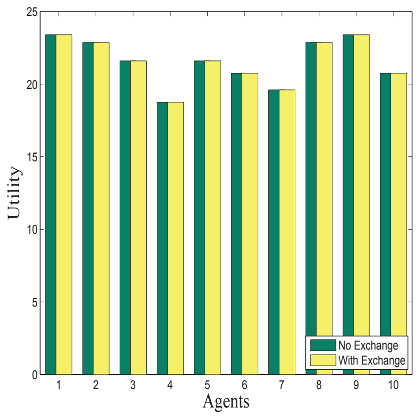
[10]Such battery specifications have been used in the related work. For example, see [17] .



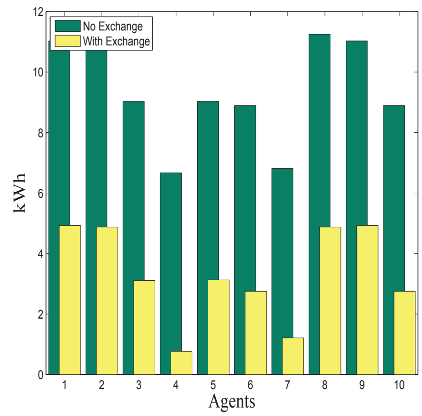
(a) Charging Shapley Value: Agents with smaller batteries contribute less.



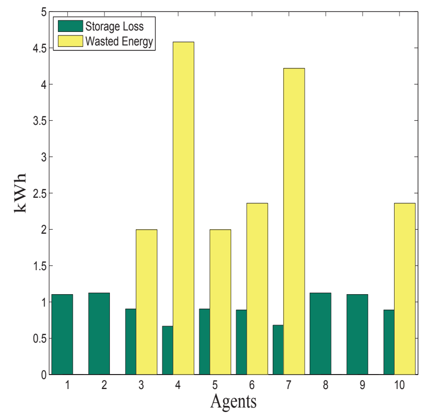
(b) Energy Shapley Values: Agents with smaller batteries contribute more.



(c) Agents maintain the same utility with and without exchange.



(d) Agents reduce their battery charging via energy exchange.



(e) Lower battery capacity mean more energy waste (when agents do not exchange energy).

Figure 2: Comparative analysis of variations and its causes in charging and energy Shapley values of agents.

agents (chosen to be close to the number of households (98) in an average Indian village [8]) to show how exchange can be scaled up.

LP Solver: All linear models are solvable with a general-purpose LP Solver and we use IBM ILOG CPLEX[11], a powerful optimiser, that provides easy and rich methods to model constraints, variables and objective functions. All experiments were run on a 3GHz machine with 12GB RAM.

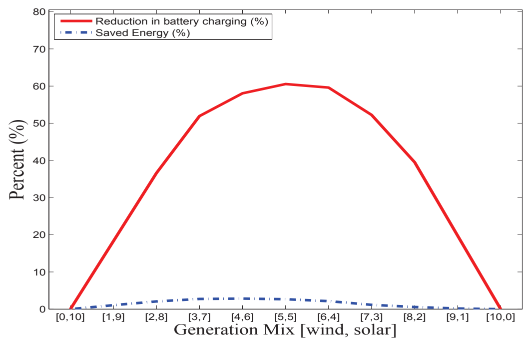
Benchmark: To the best of our knowledge, there is no study on energy exchange in cooperative communities that we could compare our results with. The state-of-the-art in terms of existing off-grid communities is just the isolated homes with some microgeneration and storage. We consider this status-quo as the benchmark and show the comparative improvements that our solutions offers.

4.2 Empirical Results

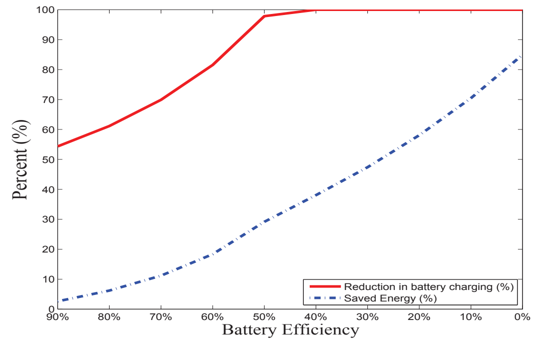
In this section, we first evaluate our model for a community of 10 agents. We compute the exact charging and energy Shapley values for all agents. Agents get different Shapley values as per their contribution and we discuss the properties (i.e., battery capacity and efficiency) that this contribution is dependent on. We then evaluate two alternate scenarios with regards to the usefulness of exchange: one to examine the effect of diversity in the generation type and the other with the reduced battery efficiency. Finally, we consider a community of 100 agents and compute the approximated Shapley values to demonstrate the scalability of our solution.

Figure 2(a) shows the exact charging Shapley values for each agent in a community of 10 agents. This is the average marginal contribution of an agent to the overall battery charging in a community. For example, agent 1 has a marginal contribution of 4.9kWh battery charging, which is the average marginal increase in the overall charging that this agent's presence causes in the community. In other words, the more the charging Shapley value of an agent, the more charging burden it is asked to take in a community. We make two important observations here. First, the charging Shapley values of agents with the same battery specification, are very similar (Figure 2(a)). Second, agents who use their batteries comparatively less (i.e., the sum of their charging is low) when they are disconnected, have a lower impact on the overall community charging and thus their batteries are used less. This may seem slightly counter-intuitive because one may think that an agent with a bigger battery can be more *useful* to a coalition. However, having a larger battery does not mean that an agent will be sharing more of its battery as constraint o_{12} guarantees them that their battery charging will not increase as a result of energy exchange. This means that the charging Shapley value of an agent is not dependent on the size of their battery. In fact, Figure 2(d) shows that an agent's charging Shapley value is dependent on its *actual* battery charging before joining the coalition. So if an agent charges its battery more when it is disconnected, compared with other agents, it will have a higher charging Shapley value in the community.

[11] IBM CPLEX is available free of cost to academia - http://www-01.ibm.com/software/integration/optimization/cplex-optimizer/

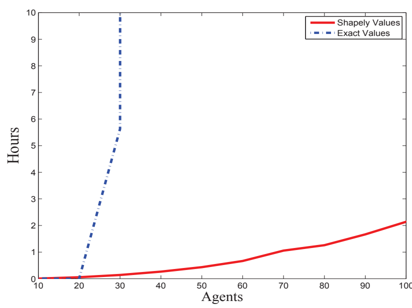


(a) More Diversity in the generation mix means more opportunities for energy exchange.

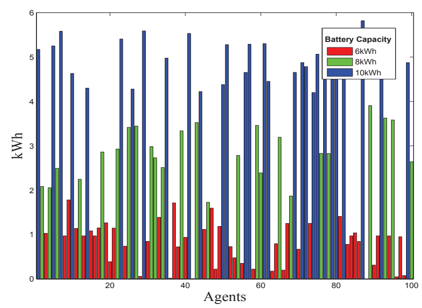


(b) As battery efficiency decreases, energy exchange becomes more useful.

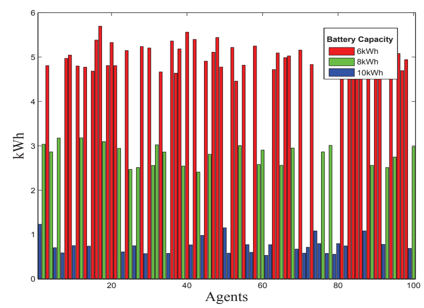
Figure 3: Alternate Scenarios: Energy exchange with regards to diversity in generation and battery efficiency.



(a) Computation time v/s number of agents.



(b) Charging Shapley value for 100 agents.



(c) Energy Shapley value for 100 agents.

Figure 4: Using approximated Shapley values for large communities.

Figure 2(b) shows the exact energy Shapley values for each agent, which is the average marginal contribution to the overall energy saving that an agent's presence in a community results in. Again, we make two observations here. First, we observe that agents with similar battery capacity have similar energy Shapley values. Second, the agents with smaller batteries contribute more towards the overall energy savings. This is because the agents with smaller batteries may have more *wasted energy* and with exchange this energy may be saved. Figure 2(e) confirms this case by showing the wasted energy and energy storage loss when agents are not connected. We can see that the agents with smaller batteries (e.g., agents 4 and 7) have more wasted energy compared to the agents with bigger batteries (agent 1 and 2) and therefore, agents 4 and 7 are the biggest contributor to the saved energy in the community. It is important to note that even when no agent has any wasted energy, the reduction in their battery charging when they exchange energy, will always yield some energy savings, unless their storage is 100% efficient.

Figure 2(c) shows the utility of agents with and without exchange. It is obvious that agents retain their utility as guaranteed by our constraint o_{11}. Figure 2(d) shows the sum of battery charging with and without exchange for each agent. We note that none of the agents are required to use more of their battery (constraint o_{12}). Put together, o_{11} and o_{12} guarantee that it is individually rational for them to participate in energy exchange.

Figure 2(d) shows the sum of battery charging with and without exchange for each agent and we note that the sum of battery charging of all agents without exchange is 93.8kWh which drops to 33.2kWh with energy exchange. This means via energy exchange, the community reduces its overall battery charging by 64.4%.

One important aspect of energy exchange is the fact that more diversity in generation and consumption opens up more ways to exchange energy. Although, consumption can be considerably diverse among the urban consumers depending on many factors (e.g., their appliances, income, family size) it can be argued whether such diversity would exist in remote communities. For example, many families in remote Indian villages own very similar electrical appliances[8] (e.g., lighting apparatus, radio). This leaves little possibility of significant diversity in consumption. However, on the generation side, this pattern can be very different, depending on the renewable generation means. For example, two homes may have similar consumption but one may have a wind turbine while the other has a solar panel. Here, we consider two extremes, one where all homes are equipped only with solar panels (no wind turbines) and one where they all have wind turbines only. Figure 3(a) shows the percentage reduction in battery charging, compared with the total battery charging with no exchange, and the percentage of energy saved, compared with the total energy usage with no exchange, when energy is exchanged. It can be seen that as the diversity in generation means increases, the agents have more opportunities to exchange energy and to reduce their battery usage, with the maximum reduction in battery charging with the most diversity. Here, we only show the saved energy that comes directly from the reduction in battery charging, to show that improvement in energy efficiency is possible even when there is no *wasted energy* in the community.

The efficiency of an electric battery degrades with usage and time. The actual dynamics of this degradation depends on a number of factors but all energy storage devices are bound to lose their efficiency over multiple charging cycles. Figure 3(b) shows what happens as the batteries (of all agents) in a community become less efficient. We know that as the battery efficiency is reduced, the energy storage loss increases. Via exchange, this energy loss can be avoided and Figure 3(b) shows that the percentage of energy saved increases as the battery efficiency decreases. Also, we note that when the agents have very inefficient batteries (40% and less efficient), exchange offers them 100% reduction in battery usage. This is because with very inefficient batteries, the storage losses ramp up and thus the agents' utilities decrease significantly. With exchange, such low agent' utilties are acheivable easily without using any storage in the community.

Figure 4 shows how our solution can be scaled up to larger communities. In particular, Figure 4(a) shows the comparison of computational time required to compute the Shapley values along with the approximated Shapley values. It is obvious that calculating the Shapley values beyond 16 agents (10.1 hours for 15 agents as shown in Figure 4(a) and it doubles for 16 agents, i.e. 21 hours) is not feasible (in reasonable time) even when the exchange takes place over a single day. In contrast, we can use the approximated Shapley values for larger communities as it scales up decently with the number of agents. Figure 4(b) and Figure 4(c) show the approximated charging and energy Shapley values for 100 agents. As mentioned in Section 3.5, *ApproShapley* needed 112 samples per agent to ensure that the approximated values are within ± 1.5 range of the actual Shapley values with a 95% chance. We note that our observations for Figure 2(a) and Figure 2(b) are valid here too. In addition, the overall battery reduction for 100 agents is 69.2% which is comparable to the community of 10 agents (64%).

5. CONCLUSION AND FUTURE WORK

Energy exchange has already been shown to be effective in the efficient use of energy and resources in some domains (e.g., utility companies [14] and smart homes [1]). Using multiagent systems and cooperative game theory, we extend this idea of exchange to communities and show that a community can reduce the battery usage (by 64%) while using energy more efficienctly (up to 80% in some cases). We have also shown that the fair distribution of the surplus can be acheived either by computing the exact Shapley value or approximated Shapley values in large communities. Our solution requires no monetary payments and thus is applicable in remote communities with no financial systems in place.

Our work can also be useful in *unit sizing* [11, 7], a process where engineers estimate the optimal size of a microgeneration unit and storage for a home. Here, connecting the home to a neighbour's or community will enable energy exchange which can help reduce the need for storage and improve the efficient use of electricity. Thus, where applicable, energy exchange can be useful unit sizing. Furthermore, our work can be beneficial for organisations (such as NGOs and governmental agencies) that are interested in providing microgeneration units to the remote communities in developing world. In this case, energy exchange can cut down the maintenance cost for such communities. Also, agent-based simulations to coordinate these resources (as we demonstrated) can be useful in finding the right mixture and combination of microgeneration units and storage to bring down the infrastructure cost.

There is also a growing interest in providing the off-grid communities with used electric batteries [5, 3], in particular, used EV batteries [9, 12].[11] Such batteries have reduced storage efficiency (e.g. an electric EV battery may have its storage shrunken by 20% after some use of years) and we showed that energy efficiency can be greatly improved by exchanging energy in such cases.

Energy generation from some renewable generation units (e.g., solar panels and wind turbines) is weather-dependent and thus it is marked with uncertainty. In future, we will extend our model to incorporate such uncertainty in generation. Furthermore, we have not considered the fact that some loads can be deferrable and our future work will include different type of loads (e.g. critical, deferrable and non-deferrable) to investigate the possibility of energy exchange in such scenarios.

[11]See PHEV/EV Li-on Battery Second-Use Project `nrel.gov/vehiclesandfuels/energystorage` and Nissan's 4R Energy project for its LEAF EV battery re-use `nissan-global.com/EN/NEWS/2011/1107.html`

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