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Efficient Allocation of Harvested Energy at the Edge by Building a Tangible Micro-Grid—The Texas Case

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Abstract—The electricity grid, using Information and Communication Technology, is transformed into Smart Grid (SG), which is highly efficient and responsive, promoting two-way energy and information flow between energy-distributors and consumers. Many consumers are becoming prosumers by also harvesting energy. The trend is to form small communities of consumers/prosumers, leading to Micro-grids (MG) to manage energy locally. MGs are parts of SG that decentralize the energy flow, allocating the excess of harvested energy within the community. Energy allocation amongst them must solve certain issues *viz.*, 1) balancing supply/demand within MGs; 2) how allocating energy to a user affects his/her community; and 3) what are the economic benefits for users. To address these issues, we propose six Energy Allocation Strategies (EASs) for MGs – ranging from simple to optimal and their combinations. We maximize the usage of harvested energy within the MG. We form household-groups sharing similar characteristics to apply EASs by analyzing energy and socioeconomic data thoroughly. We propose four evaluation metrics and evaluate our EASs on data acquired from 443 households over a year. By prioritizing specific households, we increase the number of fully served households to 81% compared to random sharing. By combining EASs, we boost the social welfare parameter by 49%.

Index Terms—Micro-girds, energy allocation strategies, harvested energy, social welfare, clustering, water filling, game theory.

I. INTRODUCTION

TRADITIONALLY, the energy distribution network (grid) is centralized. Substations are primarily used to interface centralized generators with a large number of end-users. However, the electricity grid, utilizing ICT, has been transformed into a highly efficient and responsive grid, also known as Smart Grid (SG). Further, apart from only drawing energy from the power line, some consumers harvest energy using renewable sources and are called prosumers. SG promotes the bidirectional communication between the substation and
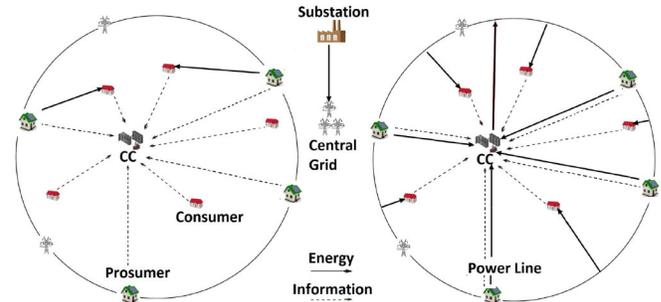
Fig. 1. Models of MG with Central Controller (CC); (left) CC used only for communication; (right) CC also has storage.

the consumers/prosumers –mostly by using Long Range Wide Area Networks (LoRaWAN) and other Low Power WANs [2]– and employs intelligent monitoring and control to manage their requirements efficiently. The above enhanced the efficiency, reliability, and sustainability of the electricity grid. SGs deploy large numbers of smart meters. These Internet-enabled devices collect fine-grained data regarding energy usage and offer real-time information to enhance efficiency in energy harvesting and distribution and bring consumption-awareness. Prosumers generate power using solar (mostly), wind, and hydro-power, which can be allocated to other customers in the vicinity. This makes SGs dynamic and less dependent on substations. However, renewable sources of energy are intermittent and require forecasting. Thus, the presence of power distribution lines of substations as stable electricity suppliers is imperative.

Micro Grids (MGs) are small communities of consumers and prosumers that have evolved to support distributed control from SGs. MGs allocate energy between consumers and prosumers while complying with policies prioritizing certain users. The energy redistribution at a local level is also economically beneficial (see Fig. 1). Buying energy from the substation is more expensive compared to getting it from the neighborhood while selling back to the substation is less lucrative compared to selling directly to neighbors [3]. To share energy at a neighborhood level, coalitions of utility companies and municipalities use storage points. They store the excess of harvested energy and supply it according to the service priorities and policies of their respective MGs. However, allocating energy among prosumers and consumers is non-trivial because of several **constraints**:

(a) individual consumers present varying energy requirements over time, and hence allocation mechanisms must be adaptive,

(b) prioritizing certain consumers causes bias in the community, therefore it is essential to develop rigorous Energy Allocation Strategies (EASs),

(c) the predictability of the amounts of harvested energy is limited as the renewable sources are intermittent, and

(d) socioeconomic characteristics (often private) affect consumption and generation of energy (e.g., size of households, income, and age of residents) [4], [5].

We propose EASs to achieve fairness, defined for particular groups of consumers or over entire MGs. Specifically, encompassing the above issues we answer the general question: **How to optimize the allocation of the excess of harvested energy between the members of a community under various constraints?** To this end, our contributions are:

1) We characterize the MG community regarding the excess and deficiency of energy of its members.

2) We propose three optimal EASs to maximize energy sharing and minimize the energy borrowed from the substation based on *game theoretic* and *information theoretic* formulations [1], [6].

3) We propose three simple EASs for MGs without centralized energy storage.

4) We demonstrate the efficacy of our proposed algorithms on a real-world dataset collected over a year from 443 households located in Texas [7].

5) We provide an analysis of the economic benefits for the members when sharing the excess of energy at a local level (MG) compared to trading with the substation.

Though we utilize commonly used methodology well-known in communications, the metrics and treatment are different and novel. This work targets the problem of sharing the energy locally in networks of energy-harvesting devices that communicate wirelessly. The idea is to provide generic frameworks spanning from simple to complex and targeting different aspects such as social welfare. This article aligns with the context of green communication and networking by providing (non-)cooperative mechanisms of energy redistribution in self-organized, dynamic communities (MGs), which involve energy-aware, although heterogeneous, members (households). We improve the energy efficiency and overall sustainability of MGs fairly, by utilizing environmentally aware methods, i.e., energy harvesting, and bidirectional communication among smart meters and energy storage utilities. This work significantly deals with the data collected from smart meters and the communication within a microgrid. The communication between the customers and Central Controller (CC) helps in bringing overall energy efficiency and also sharing amongst the consumers and prosumers. The algorithms are generic and can be used in any other situation, such as computation of off-loading to match the energy harvested, and/or edge computing, having multiple CCs working locally to stabilize the production and consumption.

The rest of the manuscript is organized as follows. A summary of the literature is provided in Section II. In Section III, we present the model of an MG and define the relations among the involved entities. In Section IV, we explain how the characterization of the community regarding energy takes place, and we explain the EASs. Further, in Section V, we present the dataset and define the metrics used for the evaluation. In Section VI, we present the characterization of the MG in energy terms, we evaluate our EASs and offer a cost analysis of sharing energy between prosumers and consumers. Section VII concludes this manuscript.

II. RELATED WORKS

Characterization: Smart meter data is used for clustering, classification, forecasting, and energy management of households. To this point, demand response strategies have been enabled by the analysis of the smart meter data at household, appliance, and occupant level [8]. Nambi *et al.* create an online demand regulation model to find the temporal dynamics of households' energy demand, using the smart meter data from more than 4000 households of a real-world SG [9]. Humala *et al.* develop individual models of energy consumption from appliances of pilot-houses and cluster them to define general models for each appliance, which are used as means of blind disaggregation of energy consumption [10]. Çimen *et al.* apply deep neural network techniques on data acquired from house-appliances to characterize the energy consumption behavior of end-users, and design a distributed system of energy management and load scheduling for residential MGs [11]. Chou and Ngo consider the energy consumed by residential buildings as time-series data consisting of linear and non-linear components, and by analyzing them they predict one-day energy consumption, to achieve energy saving in residential buildings [12], [13]. Viegas *et al.* [14] cluster data acquired from smart meters to derive the representative consumption profiles of existing customers, and then combine them with meta-data from questionnaires to characterize their behavior.

Energy Sharing: Coordination of different MGs composed of multiple households in the same area is considered in several works. The excess energy is either stored in batteries or transferred to other households or to the power grid. In independent multi-agent structures, households communicate with each other in the community regarding electricity prices and their energy profiles, whereas, in dependent multi-agent systems centralized entities control this information and influence households regarding their energy transfer decisions [15], [16]. Huang *et al.* realize direct energy sharing between nearby households by a hierarchical, three-layer system architecture. A harvesting/consumption layer uses smart meters, a prediction layer forecasts harvested/consumed energy to characterize each household as supplier/demander, and a sharing layer utilizes a greedy matching algorithm that pairs close-by suppliers and demanders and schedules energy transmissions [17]. Morstyn *et al.* propose a virtual power plant created through peer-to-peer (P2P) transactions among prosumers to incentivize them to coordinate and trade their excess energy [18]. Similarly, Long *et al.* [19] use energy sharing coordinators for households to control the energy they generate by renewables. Akter *et al.* present a distributed

energy management scheme for residential microgrids of consumers and prosumers using mixed-integer linear programming, to optimize energy management in a neighborhood [20]. Bui *et al*. introduce a multi-MG energy trading strategy, wherein MGs being in electricity shortage form pairs with those in excess to exchange energy. MGs able to generate excess at lower costs are preferred, reducing the total trading costs [21]. MG-prosumers store their excess energy in a shared storage unit for later usage in the work of AlSkaif *et al*. [22]. Reallocation of the stored energy and consumption scheduling is achieved by accounting for the historical consumption data of the households. Online energy management in networked MGs is considered in [23]–[26]. Shi *et al*. proposed a stochastic model of the power flow in MGs for real-time energy management based on Lyapunov optimization [23]. Online energy management of MGs by applying the Alternating Direction Method of Multipliers (ADMM) on the historical data of the generated energy was proposed by Liu *et al*. [24] and Ma *et al*. [25]. Liu *et al*. consider a centralized operator per MG that constructs and controls an energy exchange network between prosumers and the power grid. In contrast, Ma *et al*. consider privately owned MGs exchanging energy with adjacent MGs based on power flow constraints using the power line. Cui *et al*. analyze energy sharing in an MG as a bi-level optimization problem among retailer and prosumers with energy storage capabilities. The prosumers, applying load-shifting, follow an online optimization model with a punishment mechanism to schedule their energy usage in real-time [26]. Game-theoretic approaches are considered in [27]–[35]. Motivated by the cooperative game theory, Du *et al*. form coalitions of MGs, which coordinate the sharing of surplus in electrical and thermal energy to minimize their operational costs [27]. Yang *et al*. consider such coalitions of MGs consuming and exchanging energy according to a bi-level structure, cooperating to maintain the balance of supply-demand in the system and minimize their operational cost [33]. The economic benefits of applying a game-theoretic P2P energy trading scheme are analyzed by Tushar *et al*. [28], where a game-theoretic framework –developed on a consumer prioritization basis– is introduced for the reduction of peak to average power ratio in neighbourhoods. Anoh *et al*. group prosumers in virtual-MGs and model the energy trading interactions among prosumers and consumers as a Stackelberg game in which prosumers lead, and consumers follow [29]. Cui *et al*. design P2P energy sharing algorithms using the ADMM algorithm. Sharing is modeled as a non-cooperative game wherein equilibrium is reached between buildings regarding the prices of supply/demand of the generated energy [30]. Zhang *et al*. establish a hierarchical, four-layer system architecture for P2P energy sharing among prosumers and consumers, incorporating physical components (e.g., smart meters), communication protocols, control strategies, and non-cooperative game-theoretic bidding procedures regarding trading. Further, a software platform called Elecbay handles energy sharing among the entities [31]. Paudel *et al*. model the real-time P2P sharing in a prosumer-MG wherein sellers compete on price and amount of dispatched energy based on a non-cooperative

game, buyers select from whom they receive energy in an evolutionary game, and the interaction among sellers and buyers is modeled as a Stackelberg game [32]. Stackelberg game is also considered by Zhou *et al*. for seller-buyer interaction at MG-level. Each MG distributes/requires energy depending on the equilibrium of decisions among its non-cooperative members regarding load scheduling for utility maximization [34]. Jadhav *et al*. form clusters of MGs with excess/deficit of energy which communicate through aggregators (cluster heads). Monetary incentives are offered to MGs with excess, while deficit-MGs compete over the generated energy [35].

III. System Model

Fig. 1 depicts an abstract model of an MG neighborhood-community. From an energy perspective, MGs are sets of households with different energy needs, equipped with several electrical appliances. Because of heterogeneity in size, building type, type of appliances, and preferences/number of occupants, the energy needs are different for each household. Besides, among the households, some are prosumers generating energy through renewable sources. Note that if the households cannot cover their own needs by generating energy, the deficit is drawn from the power distribution line of the substation. In an MG community of c consumers and p prosumers, let the group of consumers be $\boldsymbol{C} = \{C_1, C_2, \ldots, C_c\}$ and, similarly, $\boldsymbol{P} = \{P_1, P_2, \ldots, P_p\}$ representing prosumers. Both $\boldsymbol{C}$ and $\boldsymbol{P}$ are connected to the power line of the substation, which is also mandatory for energy transactions between them, as $\boldsymbol{C}$ and $\boldsymbol{P}$ do not possess the infrastructure required to share energy directly. To this end, applying EASs between households is the responsibility of a central controller (CC), owned by the MG-operator (utility companies). In Fig. 1, the CC is connected to all the households, to route information about the energy needs of consumers and the amounts of energy generated by the prosumers. The decisions of CC about any energy transition are forwarded to the involved prosumers and consumers. The communication between the CC and the smart meters of the households which measure the energy consumption/generation takes place using LoRaWAN (or other Low Power WANs), due to their efficient and long range transmission capability. LoRaWAN can help in mitigating the hassles of last mile connectivity, so the CC can use authentic generation and consumption data. Specifically, CC works as the gateway to which the smart meters uplink their energy-data. Further, CC broadcasts or multicasts information to (groups of) the members of MG regarding the energy needs of other members and/or regarding changes in the energy allocation. However, apart from the MG models in which the CC is solely a communication point, there are also models in which it connects to the power line of the substation, to store and forward the excess energy from prosumers to (members of) $\boldsymbol{C}$ using the EAS-algorithms (see, right part of Fig. 1) [1], [6]. Since prosumers have their own energy needs, they cannot allocate all their generated energy to consumers. Once the total produced excess energy is stored in CCs, the CCs are
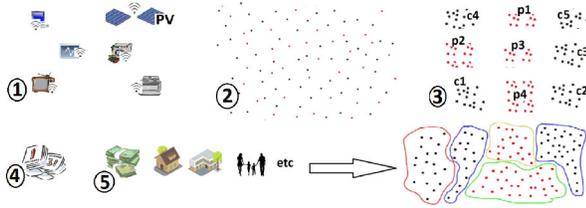
Fig. 2. Community characterization step-by-step; 1: smart meters in a single household, 2: community of prosumers (red) and consumers (black), 3: energy clustering, 4: temporal metrics, 5: meta-data.

Fig. 3. Consumption clustering (from date 1/6 to 1/12).

informed by the consumers regarding their energy requirements, $\boldsymbol{E_a} = \{E_{a,1}, E_{a,2}, \ldots, E_{a,c}\}$, and then, the dictated allocation strategy (EAS) is applied. As a result, every consumer $i \in [1, c]$ receives an amount of energy represented by $\boldsymbol{E_g} = \{E_{g,1}, E_{g,2}, \ldots, E_{g,c}\}$, to cover his/her needs partially, $E_{g,i} < E_{a,i}$, or totally, $E_{g,i} = E_{a,i}$, depending on his/her priority of service within the MG. In this work, MG communities with users having their own battery storage are not considered. Using batteries in houses incurs capital and maintenance costs. Furthermore, battery round-trip efficiency has to be taken into account, i.e., power losses during charging-discharging. We assume that the costs as mentioned above and losses are undertaken by the utility (company, business operator) that controls CC. Besides, in our study case, we assume a small neighborhood where we consider neither the losses when CC stores/distributes energy nor the physical limitations of the distribution grid, i.e., capacity limits, rapid increase of power flow on transmission lines when long-distance trading is considered.

IV. METHODOLOGY

A. Characterization

Fig. 2 depicts the steps taken to characterize the members of an MG community in terms of their energy deficiency/excess. We use fine-grained data regarding consumption of appliances and generation by renewable energy sources. Using the consumption/generation data, we compute the deficiency/excess of energy for every household. For a household i, consumption is Con_i, and generation is Gen_i. Supposing it can cover its own needs, its excess is $E_{e,i} = \mathrm{Gen}_i - \mathrm{Con}_i$, while, if it still needs energy, its deficiency is $E_{a,i} = \mathrm{Con}_i - \mathrm{Gen}_i$. The patterns of a family's daily chores affect the energy behavior of a household, varying within a day, between weekdays-weekends, and seasons. To achieve convergence, we smooth the daily (and hourly) differences in energy by averaging the measurements over weekly intervals. To associate every household with the others in its community, we use *clustering* to distribute households into different groups (clusters). The clusters are characterized by their centroids. The households with values closer to a centroid, are placed around it. Specifically, assume that the averaged values for an attribute A, over a certain time interval T, are $\overline{\boldsymbol{C_A}}^T = \{\overline{C_{A,1}}^T, \overline{C_{A,2}}^T, \ldots, \overline{C_{A,c}}^T\}$, for $\boldsymbol{C}$ consumers. After clustering, the group is defined as $\overline{\boldsymbol{C_A}}^T = \boldsymbol{Cl_{A,1}} \cup \boldsymbol{Cl_{A,2}} \cup \cdots \cup \boldsymbol{Cl_{A,m}}$, where m is the total number of clusters. The same holds for the prosumers
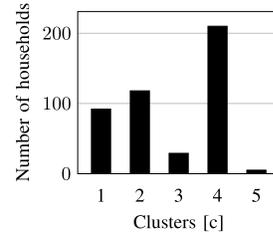
as $\overline{\boldsymbol{P_A}}^T$. A critical limitation with clustering algorithms, such as k-means, is the requirement of *a priori* knowledge on the number of clusters, which is not possible in our case. In this article, we use the *Expectation-Maximization* (EM) algorithm to define the exact number of clusters that can best accommodate the households regarding their attributes (e.g., consumption, generation), and distribute every household uniquely to one cluster (c) [36]. We utilize the EM algorithm as it derives the maximum likelihood estimates of parameters in models that depend on latent variables, i.e., the intermittency in energy harvesting and the socio-economic characteristics of the occupants. These variables, although not observable directly, affect the generation/consumption measured by the smart meters. EM clustering iteratively refines an initial clustering model to fit the data according to the principle of maximum likelihood estimation [37]. The likelihood of a household being a member of a cluster increases per iteration as we slowly reach convergence. In the end, we can define homogeneous clusters in terms of each energy attribute (consumption, generation, etc.). A household is a member of only one cluster (c) at any given time interval T and this uniquely characterizes its relationship with the other households.

For example, in Fig. 3, the energy consumption results for the second week of the year are clustered. Clusters are set in ascending order regarding their centroids, with levels increasing from c_1 to c_5 on the *x*-axis. Most of the households consumed high amounts of energy during that week (see $c4$ in Fig. 3). To acquire the energy consumption/generation perspective of households over longer periods (e.g., yearly), the metrics of temporal membership and adaptability are used. Cluster *membership* refers to the presence of a household in one of the clusters that are defined for an energy attribute and cluster *adaptability* refers to the transition between different clusters of the same attribute in consecutive time intervals (clustering periods) [1], [6], [9]. In consumption terms, a transition from high to low clusters is considered beneficial because the household saves energy and expenses. Regarding generation, a low to high cluster transition is beneficial as the prosumer shows his/her potential to generate higher amounts of energy (than other prosumers in the community), leading to a higher profit by selling it. The terms *temporal membership* and *temporal adaptability* assess the probability that a household is a member of a cluster or performs a cluster transition. Thus, for a household i, under a clustering scheme of time interval T, its temporal membership for cluster u over a long
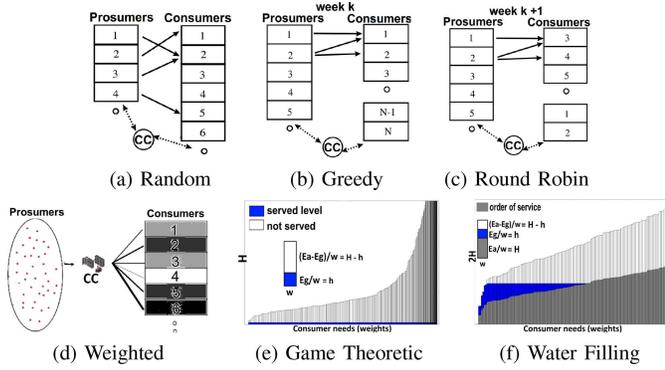
Fig. 4. Simple and Optimal Energy Allocation Strategies.

time-period (e.g., year) is defined as,

$$\mathrm{Cl}_{A,u,i} = \frac{\sum_{T=1}^{T_{\max}} \mathrm{Cl}_{A,u,i}{}^{T}}{T_{\max}}, \tag{1}$$

where, $\mathrm{Cl}_{A,u,i}{}^{T} = 1$ iff i was member of u during T (0 otherwise) and $T_{\max}$ is the number of consecutive time intervals, T, that constitute a long time-period. The temporal adaptability of a household between clusters u and v is defined in the same way as,

$$(\mathrm{Cl}_{A,u} \to \mathrm{Cl}_{A,v})_{i,z} = \frac{\sum_{T=1}^{T_{\max}} (\mathrm{Cl}_{A,u}^{T-z} \to \mathrm{Cl}_{A,v}^{T})_i}{T_{\max} - z} \tag{2}$$

where, z is the number of consecutive time intervals needed for the (series of) cluster transition(s) to happen. Further, $(\mathrm{Cl}_{A,u}^{T-z} \to .. \to \mathrm{Cl}_{A,v}^{T})_i = 1$ iff the (series of) transition(s) took place (0 otherwise). Temporal membership and adaptability are combined with *meta-data*, to derive a complete characterization of the community. Meta-data are social attributes related to non-energy characteristics, which influence the energy attributes and affect the energy-characterization of a household [4], like the income of the family or the building type. Moreover, social and energy aspects of households are usually revealed using several programs for consumption regulations that families sign with utility companies (involving monetary incentives, pro-poor programs, text feedbacks, etc.). For the analysis, we considered anonymized data.

B. Energy Allocation Strategies (EAS)

Characterization aids in segmenting households, enabling us to define and apply EASs, algorithms by which the CC distributes excess energy among the consumers. We mention simple strategies but delve more into the optimal strategies and provide in-depth discussion. For easy understanding and comparing, all the EASs are presented schematically in Fig. 4, and their algorithms are found in [6].

Simple allocation strategies create prosumer-consumer pairs, wherein energy flows from the prosumer to the consumer, using the power line. CC is used only for routing.

Random strategy: Every prosumer sends information about his/her available energy to the CC, and the CC chooses a consumer randomly to allocate the energy. If the consumer is covered fully, the remaining energy is allocated randomly to another [see Fig. 4(a)].

Greedy strategy: As seen in Fig. 4(b), the CC lists consumers in a priority sequence, and they are served as the sequence dictates. Every prosumer transfers energy to its corresponding consumer-pair by First-In-First-Served. In the greedy approach, the order of service is the same for every time interval. This order relation results in consumers being served in the same sequence at every time interval, leading to dissatisfied consumers in the community. To ensure fair energy allocation, we propose the λ *level of service*. λ is a percentage limit of service imposed on every household. When this limit is reached, the following household will be served, and consequently, more households will be served with the same amount of energy.

Round-robin strategy: This mechanism ensures that served households in an interval are moved to the end of the service sequence, as seen in Fig. 4(c). This sequence is initially created by the priority policy at $T = 1$. At $T = 2$, the algorithm moves the previously served households to the end of the service sequence (and redefines it). This mechanism continues until a predefined limit of time intervals, called *Time-Limit (TL)*, is reached. *TL* reveals the number of service rounds until reinitialization; it resets the service sequence at $T \mod TL = 0$. Consequently, *TL* defines the depth of service diversity.

In **optimal allocation strategies**, CC, besides routing, stores energy too; and computes the amount to be distributed to every consumer. Optimal EASs define *Relations of Weight* when serving the consumers. Weights are assigned to the members of C. The exact amount of energy to be received by a consumer is found using his/her weight as follows,

$$\sum_{i=1}^{p} E_{e,i} = x \sum_{j=1}^{c} w_j, \tag{3}$$

where at first, the total amount of energy that is saved by the prosumers during a time interval is gathered at CC. Then, by using the weights w given to every consumer of C, the *single unit* of energy, x, is computed, and every consumer, j, receives an amount of energy corresponding to $x w_j$. Within the community, weight-ratios between consumers dictate differences in the amounts of energy that they are entitled to. As the ratio between the assigned weights of two consumers increases, the difference in the amount of energy allocated to each of them also increases.

Weighted strategy: As seen in Fig. 4(d), the total excess energy, on every T duration, is gathered by the central controller (CC). The CC splits consumers C into N subgroups, $C = \cup_{n=1}^{N} C_n$. To each subgroup, it assigns a weight, w_n, same for all the consumers of a subgroup (n). The highest weights are assigned to the subgroups of prioritized consumers. The priority policies used by this EAS are based on size and energy (deficiency) attributes, for increased accuracy of prioritization. The energy from p prosumers is distributed according to $\sum_{i=1}^{p} E_{e,i} = x \sum_{n=1}^{N} (w_n C_n)$.

Game Theoretic strategy (GT): In GT, all the consumers seek energy according to their weights from the CC simultaneously, as shown in Fig. 4(e). They withdraw only when they are adequately served. The concept behind this algorithm relies on Game Theory, and specifically on the existence

Algorithm 1 Game Theoretic (GT)

consumer and prosumers are indexed by k and i
At the beginning:
1: CC assigns weights $w_k \forall k \in [1, c]$ according to a CPP
   At each time interval
Initialization phase:
2: CC collects excess energy from prosumers, $\sum_{i=1}^{p} E_{e,i}$
3: Consumers C send their deficiencies E_a to the CC
4: CC defines the heights of service H using $H = E_a/w$
Energy Allocation phase:
5: **while** $\sum_{k=1}^{c} H_k > 0$ **do**
6:    CC chooses non-zero minimum height of service, $\min(H)_{nz}$
7:    **if** $(\min(H)_{nz} \sum_{k=1}^{c} w_k) \leq \sum_{i=1}^{p} E_{e,i}$ **then**
8:      $E_{a,k} \leftarrow E_{a,k} - \min(H)_{nz} w_k, \quad \forall k \in [1, c]$
9:      $\sum_{i=1}^{p} E_{e,i} \leftarrow \sum_{i=1}^{p} E_{e,i} - (\min(H)_{nz} \sum_{k=1}^{c} w_k)$
10:      Consumer with $\min(H)_{nz}$ is fully served
11:      $w_{\min(H)_{nz}} = 0$
12:      $H \leftarrow H - \min(H)_{nz}$
13:    **else**
14:      $\min(H)_{nz} \leftarrow \dfrac{\sum_{i=1}^{p} E_{e,i}}{\sum_{k=1}^{c} w_k}$
15:      $E_{a,k} \leftarrow E_{a,k} - \min(H)_{nz} w_k, \quad \forall k \in [1, c]$
16:      **Break**
17:    **end if**
18: **end while**

Algorithm 2 Water-Filling (WF)

Prosumers are indexed by i
j, l represent the indices of the most and least prioritized consumer being served simultaneously
At the beginning:
1: CC assigns weights $w_k \forall k \in [1, c]$ according to a priority policy
   At each time interval
Initialization phase:
2: CC collects the excess energy from prosumer, $\sum_{i=1}^{p} E_{e,i}$
3: C send info on their deficiencies E_a to the CC
4: CC defines initial heights of service by $H = E_a/w$ and forms them in ascending order, H_{ini}
5: $j = 1, l = 1$
6: $H \leftarrow H_{ini}$
Energy Allocation phase:
7: **while** $j \leqslant c$ **do**
8:    Perform **GT** algorithm for energy allocation phase on the following:

$$\begin{cases} \text{group of } (l+1-j) \text{ consumers with weights assigned in} \\ \text{step 1 with } \sum_{i=1}^{p} E_{e,i} \text{ and additional heights } h \\ \text{if} \quad l+1 \leqslant c, h_k = \begin{cases} H_{l+1} - H_k, \text{if} \quad H_{l+1} < 2H_{ini,k} \\ 2H_{ini,k} - H_k, \quad \text{otherwise} \end{cases} \\ \text{else} \quad h_k = 2H_{ini,k} - H_k \\ \text{for} \quad k:[j, l] \end{cases}$$

After GT algorithm:
9:    Total excess decreased, $\sum_{i=1}^{p} E_{e,i}$ updated
10:    Individual deficiencies of $(l+1-j)$ households decreased or covered, $E_{a,k}$ updated $\forall k \in [j, l]$
Updating the Heights of service:
11:    $a \leftarrow j$
12:    **for** $k : [a, l]$ **do**
13:      $H_k \leftarrow H_k + h_k,$
14:      **if** $H_k = 2H_{ini,k}$ **then**
15:        $j \leftarrow j + 1$
16:      **end if**
17:    **end for**
18:    **if** ($H_l = H_{l+1}$ or $H_l = 2H_{ini,l}$) and $l+1 \leqslant c$ **then**
19:      $l \leftarrow l + 1$
20:    **end if**
21: **end while**

of an *equilibrium* based on the choices of non-cooperative consumers-players on energy allocation, where everyone is bound to a specific decision. After assigning a different weight, w, to each consumer according to the imposed priority policy, the CC, holding information about the deficiency of all the consumers, defines the ratios of deficiency and weight, termed *Levels of Service*, $H = E_a/w$. The amounts of energy that are individually received fit into the specific energy and socioeconomic characterization of each consumer. Assuming non-cooperative consumers, the equilibrium exists since no consumer has any gain from abstaining from requesting energy, but instead loses his/her share of energy by others. Consequently, we reach a stable state wherein everyone requires energy, and no one changes his/her strategy.

Water-Filling strategy (WF): At the beginning, different weights are given to each consumer by the CC depending on the priority policy that is followed. Then, being informed regarding the deficiency of each consumer, the CC defines their H. However, in this EAS, the CC arranges the H of the consumers in ascending order, which becomes their order of service. The difference between this algorithm and the GT is that some consumers can ask for energy before others. Many consumers often have to wait until the prioritized households are fully covered, as can be seen in Fig. 4(f). Let us assume that the transferred energy is added on top of the H of every consumer, as *additional service-level*, $h = E_g/w$. As the CC starts sharing energy with the first consumer in the order of service, its level h_1 increases until $h_1 = H_2 - H_1$. Then, assuming there is enough excess energy stored, the CC starts transferring to the second consumer in the order too; until $h_2 = H_3 - H_2 = h_1 - (H_2 - H_1) \Rightarrow h_1 = H_3 - H_1$. This procedure continues until the need of every consumer is covered or the energy is depleted. A consumer j is withdrawn

from service only when fully covered ($h_j = H_j$). For two consumers, j and l, with $H_l > H_j$, it is also possible that $H_l - H_j \geq H_j$, and thus the consumer j is fully covered before l starts requesting for energy. Several consumers can be served simultaneously at any time instance, as long as they have equal sums of H and h [see Fig. 4(f)]. Table I states the main advantages differentiating each EAS from the others.

In **Two-stage Approaches**, we apply one EAS to distribute the generated energy to the different consumer groups, as

TABLE I
SIMPLE AND OPTIMIZED EASs

EAS	Advantage
Random	Useful for households with similar energy trends
Greedy	Straightforward service of prioritized consumers
Round-Robin	Increases the service diversity, while maintaining the priority given by the service sequence
Weighted	Group-wise energy allocation using different weights
GT	Individually fair; realistic for non-cooperative consumers
WF	Guarantees fairness of service in the community; combines accuracy (weights) with priority (sequence)

an *inter-group* distribution, and then a second EAS to distribute the corresponding received amount of energy within every group (to every member), as an *intra-group* distribution. The advantage of two-stage approaches is the combination of different EASs, fitting the needs of every group and consumer.

V. EXPERIMENTAL EVALUATION

To test our EASs, we employed the readily available and standard Pecan Street dataset, which is located in Texas Austin and composed of 443 households. Among them, 180 households generate energy using solar panels. We used one year of consumption and generation data (in kW) from the smart meters of all the households, and computed the deficiency and excess of energy for every household. The smart meters offered fine-grained data for accurate analysis. We only selected those households having data for more than 300 days. At first, we analyzed the metrics that focus on households being served. These metrics refer to the consumers of an MG community. Thus, for a consumer k, we answer with 1 (true) or 0 (false) the following questions; **(a)** Is k served fully?, **(b)** Is k not served at all?, **(c)** Is it the first time that k is served in timespan T?

To quantify the potential of a strategy in covering completely the needs of (a group of) consumers c within a community, we define the *Served Ratio* (SR) metric for T as, $\mathrm{SR} = (\sum_{k=1}^{c} C_{\mathrm{served},k})/c$ where, $C_{\mathrm{served},k} = 1$ if consumer $k \in [1, c]$ is *fully* served, 0 otherwise. If SR is averaged, we can draw insights into the long-term serving potential of an EAS. To evaluate the efficiency of prosumers in serving (a group of) consumers during T, we define the *Prosumers Beneficial Ratio*, $\mathrm{PBR} = (\sum_{k=1}^{c} C_{\mathrm{notServed},k})/p$ where, $C_{\mathrm{notServed},k} = 1$ if consumer $k \in [1, c]$ is *not at all* served, 0 otherwise. If PBR is averaged, we can draw insights into the way an EAS utilizes the prosumers over a number of consecutive time intervals. Low values of PBR imply efficient prosumer usage. For the EASs that use priority sequences for consumer service, we use *Uniqueness Ratio* (UR), which quantifies the service diversity of a sharing strategy for (a group of) consumers for any set of consecutive time intervals, denoted as $T_b - T_a$, with $T_a, T_b \in [1, T_{\max}]$. $\mathrm{UR} = (\sum_{T=T_a}^{T_b} \sum_{k=1}^{c} C_{\mathrm{unique},k}^T)/c$ where, $C_{\mathrm{unique},k} = 1$ if it is the *first time* that a consumer $k \in [1, c]$ is served during $T_b - T_a$, 0 otherwise.

To quantify satisfaction regarding the service offered to a consumer during a timespan T, we use the ratio of the amount of energy given to a household (or a group) and its total energy sought. We term this ratio *Energy Ratio* (ER) and, for a consumer k, during T, the ER is defined as, $\mathrm{ER}_k = E_{\mathrm{g},k}/E_{\mathrm{a},k}$. When $\mathrm{ER} = 0$, no energy is received. However, to evaluate fairness in service we have to consider the priority that every household possesses within its group. Under a priority policy, the coverage of deficiency of every household impacts the community differently. Prioritized households are more critical in terms of service and should receive higher amounts of energy than the rest. For a consumer k, applying a weight that mirrors his/her significance in the community turns ER into its weighted form, $\mathrm{ER}_{w,k} = w_k \mathrm{ER}_k$. To evaluate it, we use the
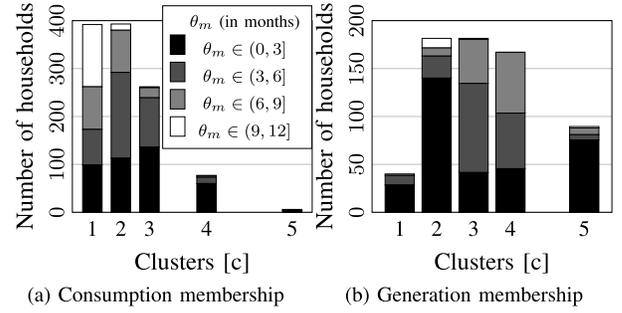

Fig. 5. Temporal membership behaviors.

$\log_2$ relation to define the *Social Welfare* (SW) for any consumer k, $\mathrm{SW}_k = w_k \log_2(1 + \mathrm{ER}_k)$. However, SW_k cannot be characterized as high or low and thus fairness in serving consumers according to their significance cannot be evaluated by SW. It needs to be compared with the maximum possible value of SW_k. Obviously, when a consumer is fully served $\mathrm{ER}_k = 1$, then $\mathrm{SW}_{k,\max} = w_k$. Thus the metric to characterize every consumer regarding the fairness in energy allocation is the *Social Welfare Ratio* (SWR), defined as $\mathrm{SWR}_k = \mathrm{SW}_k/w_k$. In order to expand the individual-SW to group-SW, or further, to SW for a whole community of c consumers, the aforementioned $\log_2$ relation gives $\mathrm{SW}_c = \sum_{k=1}^{c} \mathrm{SW}_k$. This term will be maximum when all the consumers are served completely, i.e., $\mathrm{SW}_{\max,c} = \sum_{k=1}^{c} w_k$. Thus, the community SWR is, $\mathrm{SWR}_c = (\sum_{k=1}^{c} \mathrm{SW}_k)/(\sum_{k=1}^{c} w_k)$. For a given amount of excess energy, the SWR of c consumers increases rapidly when the prioritized consumers receive higher amounts of energy than the rest because these consumers possess the highest weights within their community.

VI. IMPLEMENTATION RESULTS

A. Energy Behavior

We evaluate the temporal energy behavior of households using membership and adaptability. In Fig. 5(a), the x-axis shows the clusters in terms of consumption; c_1 represents low consumption and c_5 high. Further, the position of the clusters on x-axis represents cluster centroids. The yearly membership ratio for a household being in a particular cluster is θ_m. In Fig. 5(a), about 400 households consumed low amounts of energy, out of which, 115 households were in c_1 for more than 75% of the year (white). This result implies that 115 households can be prioritized by policies that focus on low deficient consumers. Regarding generation, 100 out of 180 prosumers generated a satisfactory amount of energy, distributed over c_3 and c_4 for more than six months [see Fig. 5(b)]. This implies the following: 1) these 100 households are more efficient than the other prosumers and 2) they present low consumption membership because they cover their needs partially by using their own generated energy.

In Fig. 6(a), the x-axis presents the beneficial cluster transitions in consumption. For a household, the ratio of particular cluster transitions (x-axis) over all the performed transitions is θ_t. Direct transitions between two non-consecutive clusters (e.g., c_3 to c_1) are rare, because they demand higher
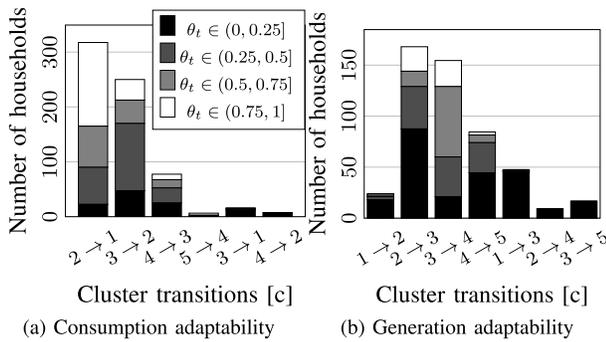
(a) Consumption adaptability

(b) Generation adaptability

Fig. 6. Temporal adaptability behaviors.

(a) Consumption membership - building types

(b) Deficiency membership - size

(c) Generation adaptability - programs

Fig. 7. Energy and socioeconomic behavior.

(a) Greedy, $\lambda = 0.5$

(b) Round-robin, 24-week TL

Fig. 8. Served households according to different priority policies and λ levels of service.

energy regulation potential from the households. As shown in Fig. 6(a), most of the households regulate their consumption between c_1, c_2, and c_3; this explains the higher numbers of households in these clusters [Fig. 5(a)]. Similarly, for prosumers from Fig. 5(b) and Fig. 6(b), it is observed that cluster transitions occur mostly between c_2, c_3, and c_4. After considering the energy behavior of the households over the year, we looked into socioeconomic attributes, to characterize them more accurately. In Fig. 7(a), three different building types of households, apartments (AP), single-family homes (SF), and town-homes (TH), are studied with respect to temporal membership for their consumption. It is inferred that apartments (cyan) cannot generate any energy, and along with the town-homes (green) they consume the lowest amounts of energy in the community. Regarding household-size, as the deficiency clusters increase from c_1 to c_4, the average floor area (in sq. ft) of the corresponding households that are members of such clusters increases, as seen in Fig. 7(b). Thus, small types of households (apartments and town-homes) are members of lower deficiency-clusters.

As seen in Fig. 7(c), households enrolled in programs for low-income families like Verizon (purple) did not generate any energy. Households enrolled in pricing incentive programs (orange) generate energy more efficiently than the rest.

B. Energy Allocation

Naturally, efficient prosumers perform many transitions in high excess-clusters while efficient consumers can regulate their consumption, and stay in low deficiency-clusters. In Fig. 8(a), we compare different priority policies for the greedy allocation strategy. Generally, by choosing policies that prioritize the less deficient consumers, we manage to serve more households than by promoting the highly deficient ones, because the prioritized households are easily served. On the contrary, high deficiency policy aims to serve those in high needs requiring large amounts of excess energy. Furthermore, by prioritizing small-sized households like the apartments, we get similar results as if the low deficient ones were prioritized. Similarly, prioritizing high deficient households is nothing but prioritizing large households [see Fig. 8(a)]. The performance of the random policy stays between other policies, as it gives priority to none. The impact of the combination of different λ levels and a round-robin approach to energy sharing
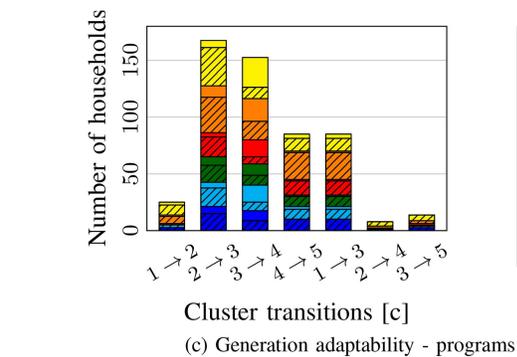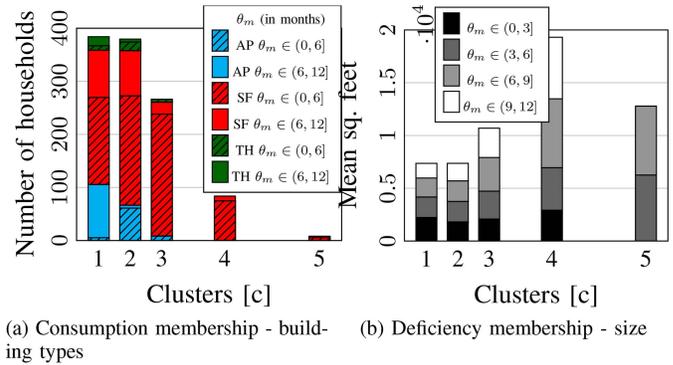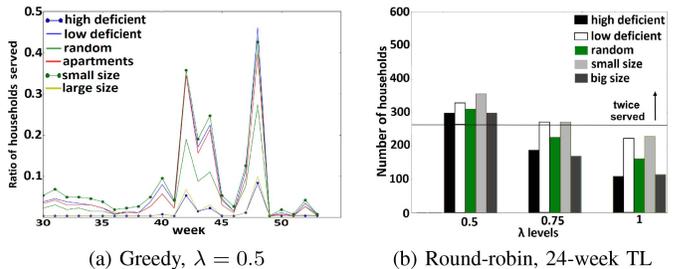
is seen in Fig. 8(b). As the λ decreases, more households are served. However, the connection between size and deficiency regarding priority policies remains same as in Fig. 8(a).

In Fig. 9(a) and Fig. 9(b), we present SR for different target groups of consumers, created based on energy deficiency and size. These groups are served for three consecutive months, using round-robin and greedy EASs. As seen in Fig. 9(b), round-robin EAS serves households from different groups– not only from the prioritized ones.

Moreover, under the round-robin strategy, because of the repositioning of highly deficient consumers at the end of the service sequence, high deficiency and large size priority policies serve more households. The opposite happens for the policies prioritizing small and less deficient consumers. In Fig. 10, the weighted EAS is presented. Each of the eight groups that are created by the combination of size and deficiency of households receives a different weekly percentage of the stored excess energy. High differences in group-weights prioritize consumers strictly, while low differences distribute
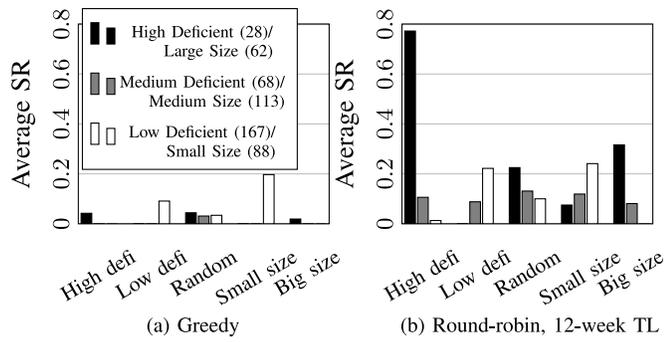
Fig. 9. Average SR based on different priority policies (numbers in parentheses are the members of each group).
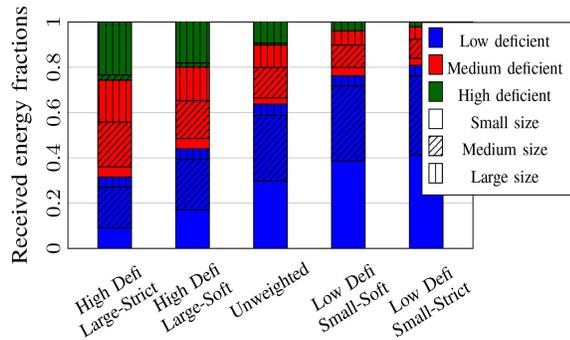

Fig. 10. Fraction of total energy received weekly by different groups - Weighted. High ratio between weights (strict): $1 \rightarrow 8$ (step 1.0), Low ratio between weights (soft): $1 \rightarrow 3.33$ (step 0.333)
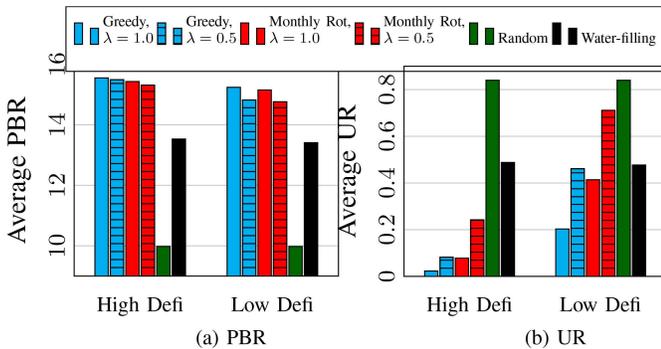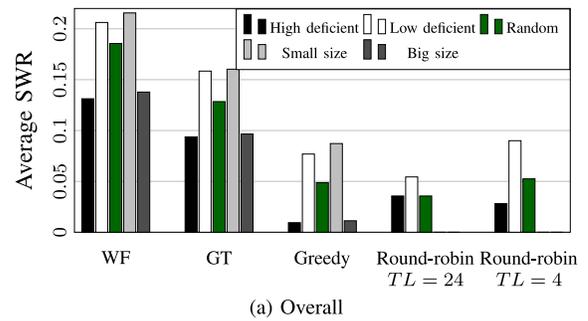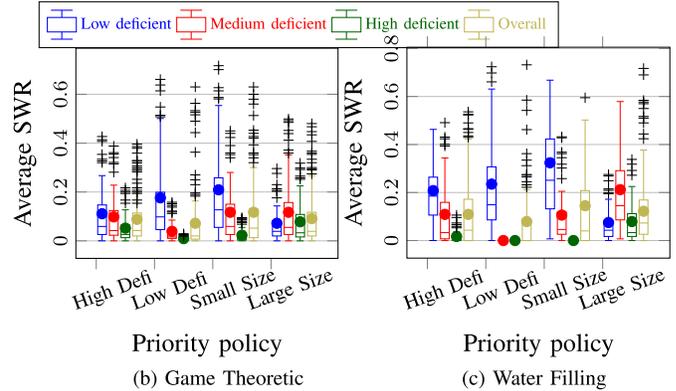

Fig. 11. Prosumer usage – Service diversity (week 38-49).

Fig. 12. Community social welfare ratio (yearly).

the excess energy more equally, resembling the unweighted approach.

In Fig. 11(a) and Fig. 11(b), we evaluate how efficiently the prosumers are used (PBR) and how diverse is the consumer service. Note that the lowest values present the most efficient behaviors as the PBR metric is related to the consumers *not* served weekly by the prosumers. Among the EASs that serve consumers in sequential order, the WF sharing approach utilizes the prosumers more efficiently than the other approaches, keeping at the same time a satisfactory UR [$\simeq 0.5$, Fig. 11(b)]. Because of no priority in serving, the random approach has much lower PBR [Fig. 11(a)] and high diversity; serving almost 85% of the consumers [Fig. 11(b)]. Service-fairness in a community is described by the SWR metric. In Fig. 12(a), the advantage of optimal algorithms against the

simple approaches on energy sharing is clear –they provide higher fairness in service for every particular priority policy. Specifically, for the WF and GT EASs, under the same policy, weights, deficiency, and stored energy, WF EAS manages higher SWR. Focusing only on these two EASs, in Fig. 12(b) and Fig. 12(c), their impact on different groups of households (which have been assigned with the same priority weights) is observed. WF prioritizes the targeted household groups stricter –maximizing SW for the members of these groups. On the other hand, in GT strategy the social welfare results for different groups of households are closer because all households receive energy simultaneously. Note here that the big-sized or the highly deficient groups of households present deficiencies that are not covered easily, thus the impact of their weights in SWR is lower than the impact of other groups when they are prioritized. The WF approach presents overall higher SWR results per priority policy, as confirmed by Fig. 12(a). Further, the GT EAS is more stable than WF, because in WF we observe more outliers.

Regarding two-stage approaches, after testing all combinations of allocation strategies, we propose the Game-Theoretic EAS for inter-group energy allocation and the Water Filling EAS for intra-group allocation. GT applies to energy distribution at a group-level because different groups of consumers, having different needs and characteristics, would demand energy selfishly, according to their weights. However, in intra-group allocation, households would cooperate under WF because they share the same needs, as is proven during the characterization procedure. As observed in Fig. 13, although the prioritized groups of consumers receive the most substantial part of the excess energy [i.e., the low deficient consumers in Fig. 13(a) and the high deficient consumers in Fig. 13(b)],
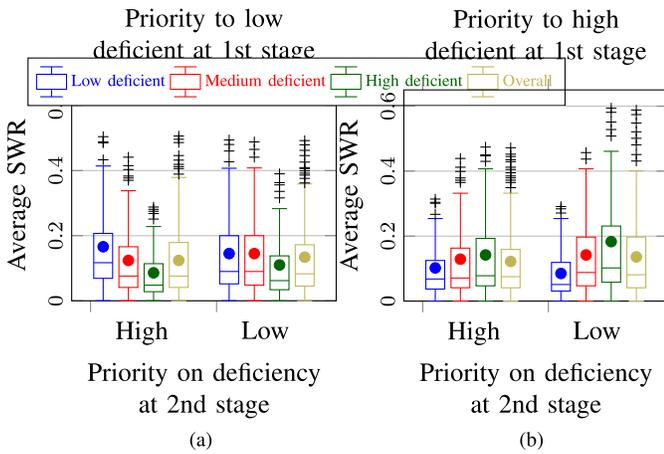
Fig. 13. Two stage energy sharing – GT for groups (1st stage), and WF individually (2nd stage).
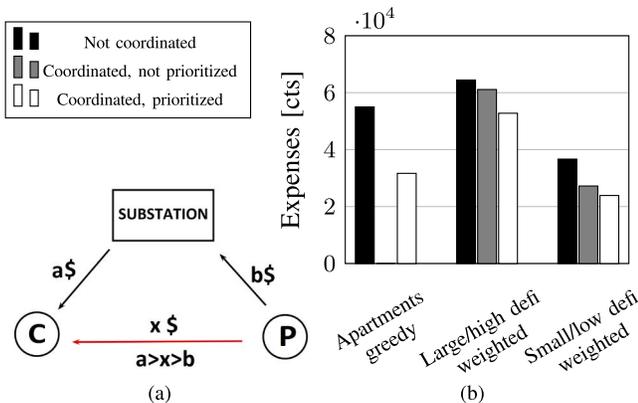

Fig. 14. (a) Cost schema; C: consumer, P: prosumer, (b) expenses reduction; pricing comparison from 10/13 to 10/26.

there is a balance regarding the amount of allocated excess to each group, contrary to Fig. 12(c).

C. Cost Analysis

In this section, we employ a standard pricing day from the Power Smart Pricing site with hourly costs per kW and use it to reproduce the expenses in case the community utilizes solely the power line between 13th and 26th of October – a period in which relatively high production of energy was observed on the prosumers side [38]. Then, we compare with the expenses when applying our EASs. By allocating the generated energy, consumers experience price-reduction for covering their deficiency, buying energy for lower prices than they would do from the substation. Further, prosumers profit from sharing, selling generated energy at higher prices to the consumers of the neighborhood than to the utilities (substation), as depicted in Fig. 14(a). We do not consider the cost of energy storage individually, locally at the CC, and/or the cost of energy losses over the wire. It is assumed that these costs are taken into account when prosumers sell excess energy to consumers [see $x\$$ in Fig. 14(a)], increasing the price at which the excess energy is sold to balance those costs. As the distribution range

increases, so do the charging/discharging losses at the storage points, leading to an increase in selling prices from the prosumers until they reach the price at which the substation sells. In Fig. 14(b), the cost reduction using weighted EAS is observed for the prioritized groups of households for different priority policies. In addition, note that energy sharing is beneficial for every consumer irrespective of the priority policy. In Fig. 14(b), although the cost reduction is higher for the prioritized groups of households (white), still there is a considerable reduction in expenses for the less prioritized consumers who received lower amounts of energy (gray).

D. Discussion

In the literature, we see that many algorithms proposed for energy allocation are based on simulated data or numerical case-studies [20], [22]–[24], [26]–[30], [32], [34], [39]. A few proposals used real data sets, but they are either not fine-grained enough [14], or not using meta-data [9]. Since meta-data provides important information, EASs cannot be agnostic towards them. Our methodology is applied to real-case data, considering 443 households, per minute consumption/generation, and socioeconomic attributes. Further, we did not encounter in the literature any combination of energy allocation strategies in two-stage approaches, which we propose and evaluate in this work. With the results, we can indeed see that there is no general prioritization technique and EAS pair that can address all the cases or requirements. This is mainly because the energy needs of households and communities keep varying while energy harvesting at a given time also varies. However, with this study, one can gather insights into MGs and EASs to make better decisions.

Expecting every household to be a prosumer in the future it will be interesting to evaluate the scaling potential of our EASs in a system of distributed MGs and/or generally in systems of harvesting devices that can be considered as separate communities. Instead of characterizing each household based on its energy attributes, a whole MG can be characterized based on the behavior of its members. Furthermore, in such a way a residential neighborhood with lots of prosumers can be split into homogeneous MGs. However, new bidding/pricing mechanisms need to be devised, probably based on non-cooperative game-theoretic approaches, as the energy transfer and the economic interaction will be extended from the level of a single MG-central grid to the level of multiple MGs-central grids. Recently more datasets are being added and also more real-time data is becoming available. It would be interesting to use our EAS-algorithms on such datasets and possibly some refinements are expected. Finally, the policies that each household follows regarding energy consumption should be following the general policy of its MG.

VII. Conclusion

With the growing adoption of energy harvesting techniques using renewable energy sources, consumers and prosumers can redistribute energy efficiently. ICT infrastructures provide the means of communication (e.g., LoRa, NB-IoT) needed to share the available energy locally, avoiding energy-transportation

losses. In addition, prosumers have higher economic benefits by selling excess energy locally compared to selling it to the central stations. In this article, we proposed and evaluated six EASs that could be easily computed at the edge of SGs, which control the allocation of the excess of harvested energy in an MG community. We considered many novel approaches, such as using both fine-grained energy-data and social attributes to exploit the temporal energy dynamics of communities. We clustered households into multiple groups, thereby making it easy to analyze the complex behavior of the community. We show that there is no "*one-size-fits-all*" strategy when prioritizing households and distributing the excess energy in an MG since the energy needs of households in a community keep varying while harvested energy also varies. We analyzed one year of data from 443 houses to test our algorithms and their impact. The most optimal allocation strategy was WF, having the highest social welfare ratio, higher by a factor of 2.5 compared to greedy approaches. This work provides many knobs to control energy allocation under various scenarios with different focuses. Although we applied our EAss to Pecan Street dataset to demonstrate the efficacy of the proposed algorithms, the ideas are generic and it can be used in any small community involving consumers/prosumers.

ACKNOWLEDGMENT

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