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Efficient Power Sharing at the Edge by Building a Tangible Micro-Grid – the Texas Case

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***Abstract*—Information and Communication Technology (ICT) is now touching various aspects of our lives. The electricity grid with the help of ICT is transformed into Smart Grid (SG) which is highly efficient and responsive. It promotes two-way energy and information flow between energy distributors and consumers. Many consumers are becoming prosumers by also producing energy. The trend is to form small communities of consumers and prosumers leading to Micro-grids (MG) to manage energy locally. MGs are parts of SG that decentralize the energy flow by allocating the produced energy within the community. Energy allocation amongst them needs to solve issues *viz.,* (i) how to balance supply/demand within micro-grids; (ii) how allocating energy to a user affects his/her community. To address these issues we propose six Energy Allocation Strategies (EASs) for MGs – ranging from simple to optimal. We maximize the usage of the energy generated by prosumers within MG. We form household-groups sharing similar characteristics to apply EASs by analyzing thoroughly energy and socioeconomic data of households. We propose four metrics to evaluate EASs. We test our EASs on the data from 443 households over a year. By prioritizing specific households, we increase the number of fully served households up to 81% compared to random sharing.**

I. Introduction

Traditionally, the energy distribution network (grid) is centralized. Substations are primarily used to interface centralized generators to a large number of end-users. Further, the electricity grid, utilizing ICT, is now transformed into a highly efficient and responsive grid, also known as Smart Grid (SG). Apart from drawing energy from the power line some consumers generate energy using renewable sources and are called prosumers. To manage the requirements of prosumers and consumers efficiently, SG employs intelligent monitoring, control, and bidirectional communication. This 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 generation and distribution and bring consumption-awareness. Prosumers generate power using solar (mostly), wind, hydro, etc., which can be allocated to other customers in the vicinity. This makes SGs dynamic and less dependent on the substation. 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

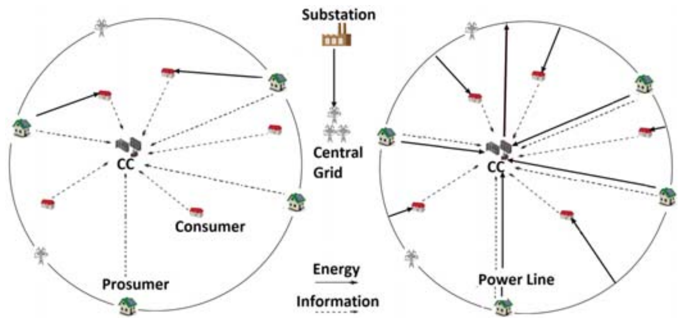

Fig. 1: Models of MG with Central Controller (CC); (left) CC used only for communication; (right) CC also has storage.

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 neighbourhood while selling back to the substation is less lucrative compared to selling directly to neighbours [1]. To share energy at a neighborhood level, storage point coalitions of utility companies and municipalities are used. They keep the generated excess 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**: (i) individual consumers present varying energy requirements over time, and hence allocation mechanisms need to be adaptive; (ii) prioritizing certain households causes bias in the community, therefore it is essential to develop rigorous Energy Allocation Strategies (EASs); (iii) the predictability of the generated energy is limited; and (iv) socioeconomic characteristics (often private) affect consumption and generation of energy (e.g., size of households, income, and age of residents) [2], [3]. We propose EASs aiming 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 produced energy excess between the members of a community under various constraints?**

To this end, (a) 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 [4]; (b) we propose three simple EASs for MGs without centralized energy storage; (c) we demonstrate the efficacy of our proposed algorithms on a real-world dataset collected over a year from 443 households located in Texas [5]. Though we use some commonly used methodology

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well-known in communications, the metrics and treatment are different and novel. **This work targets the problem of sharing the energy locally and the intricacies involved therein rather than the grid related issues.**

II. Related Works

Morstyn *et al.* propose a virtual power plant created through P2P transactions among prosumers in order to incentivize them to coordinate and trade their excess energy [6]. Similarly, in [7] individual households control the energy they generate through renewables by an energy sharing coordinator. Prosumers of a micro-grid store their excess energy in a common storage unit for later usage in [8], and a function that accounts for the historical consumption data of the households is designed to re-allocate the stored energy in households and to schedule their consumption. The problem of online energy management in networked MGs is considered in [9]–[11]. Shi *et al.* propose a stochastic model of the power flow in MGs for real-time energy management based on Lyapunov optimization [9]. Online energy management of MGs by applying the Alternating Direction Method of Multipliers (ADMM) on the historical data of the generated energy is proposed in [10], [11]. Liu *et al.* consider a centralized operator per MG that constructs and controls an energy exchange network between prosumers and the power grid, while Ma *et al.* consider privately owned MGs exchanging energy with adjacent MGs based on power flow constraints using the power line. Game-theoretic approaches are considered in [12], [13]. Motivated by the cooperative game theory, Du *et al.* form coalitions of MGs, which coordinate sharing of surplus in electrical and thermal energy in order to minimize their operational costs [12]. The economic benefits for households applying a game-theoretic peer-to-peer energy trading scheme are analyzed in [13], where the aforementioned coalitions among different prosumers are proven to be stable. The majority of works above use community-simulators and numerical case studies to apply energy allocation strategies [8]–[10], [12], [13], however, we incorporate many methods well-known in ICT domain with new metrics on a real-case data set to propose new energy sharing strategies.

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 a number of electrical appliances. In addition, 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 $\boldsymbol{C} = \{C_1, C_2, ..., C_c\}$ and, similarly, $\boldsymbol{P} = \{P_1, P_2, ..., P_p\}$ 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, the role of 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. 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 (cf., right part of Fig. 1) [4]. 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 informed by the consumers regarding their energy requirements, $\boldsymbol{E}_{\mathrm{a}} = \{E_{\mathrm{a},1}, E_{\mathrm{a},2}, ..., E_{\mathrm{a},c}\}$, 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 $\boldsymbol{E}_{\mathrm{g}} = \{E_{\mathrm{g},1}, E_{\mathrm{g},2}, ..., E_{\mathrm{g},c}\}$, to cover his/her needs partially, $E_{\mathrm{g},i} < E_{\mathrm{a},i}$, or totally, $E_{\mathrm{g},i} = E_{\mathrm{a},i}$, 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 aforementioned costs and losses are undertaken by the utility (company, business operator) that controls CC. In addition, 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 (seen in larger residential areas).

IV. Methodology

A. Characterization

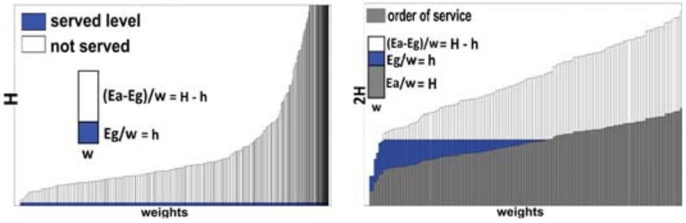
We use fine-grained data regarding consumption of appliances and generation by renewable energy sources. Using the consumption/generation data, we compute the deficiency/excess of energy for every household. To achieve convergence, we smooth the daily (and hourly) differences in energy by averaging the measurements over weekly intervals. To associate every household with the others in its community, we use *clustering* to distribute households into different groups (clusters). In this paper, 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). To acquire energy consumption/generation perspective of households over longer periods of time (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) [4], [14]. The terms *temporal membership* and *temporal adaptability* assess the probability that a household is a member of a cluster or performs a cluster transition. For the analysis, we considered anonymized data.

B. Energy Allocation Strategies (EAS)

To show the evaluation of strategies, we mention simple strategies but delve more into the optimal strategies and provide in-depth discussion. All EASs are found in [4].

Simple allocation strategies create prosumer-consumer pairs, and the energy flows from the prosumer to the consumer of each pair, 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 randomly a consumer to allocate the energy. If the consumer is covered fully, the remaining energy is allocated randomly to another.
Greedy strategy: The CC lists consumers in a priority sequence and they are served as the sequence dictates. Energy is transferred by every prosumer 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. 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 $\boldsymbol{C}$. The exact amount of energy to be received by a consumer is found using his/her weight as follows, $\sum_{i=1}^{p} E_{\text{e},i} = x \sum_{j=1}^{c} w_j$, 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 $\boldsymbol{w}$ given to every consumer of $\boldsymbol{C}$, the *single unit* of energy, x, is computed, and every consumer, j, receives an amount of energy corresponding to xw_j [4]. 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.



(a) Game Theoretic (b) Water Filling

Fig. 2: Optimal Energy Allocation Strategies

Weighted strategy: The total excess energy, on every T duration, is gathered by the central controller (CC). The CC splits consumers $\boldsymbol{C}$ into $\boldsymbol{N}$ subgroups, $\boldsymbol{C} = \cup_{n=1}^{N} \boldsymbol{C_n}$. 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 excess energy from p prosumers is distributed according to $\sum_{i=1}^{p} E_{\text{e},i} = x \sum_{n=1}^{N} (w_n \boldsymbol{C_n})$.

Algorithm 1: Game Theoretic (GT)

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

Game Theoretic strategy (GT): In GT all the consumers seek energy according to their weights from the CC simultaneously, as shown in Fig. 2a. They withdraw only when they are fully served. The concept behind this algorithm relies on Game Theory, and specifically on the existence of an *equilibrium* based on the choices of non-cooperative consumers-players on energy allocation, where everyone is bound to a certain decision. After assigning a different weight, $\boldsymbol{w}$, to each

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 CPP

At each time interval

Initialization phase:

2: CC collects the excess energy from prosumer, $\sum_{i=1}^{p} E_{\text{e,i}}$

3: $\boldsymbol{C}$ send info on their deficiencies $\boldsymbol{E}_{\text{a}}$ to the CC

4: CC defines initial heights of service by $\boldsymbol{H} = \boldsymbol{E}_{\text{a}}/\boldsymbol{w}$ and forms them in ascending order, $\boldsymbol{H}_{\text{ini}}$

5: $j = 1, l = 1$

6: $\boldsymbol{H} \leftarrow \boldsymbol{H}_{\text{ini}}$

Energy Allocation phase:

7: **while** $j \leqslant c$ **do**

8: Perform **GT** algorithm for energy allocation phase on the following:

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

After GT algorithm:

9: Total excess decreased, $\sum_{i=1}^{p} E_{\text{e,i}}$ updated

10: Individual deficiencies of $(l+1-j)$ households decreased or covered, $E_{\text{a,k}}$ 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** $H_k = 2H_{\text{ini},k}$ **then**

15: $j \leftarrow j + 1$

16: **end if**

17: **end for**

18: **if** ($H_l = H_{l+1}$ or $H_l = 2H_{\text{ini},l}$) and $l + 1 \leqslant c$ **then**

19: $l \leftarrow l + 1$

20: **end if**

21: **end while**

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*, $\boldsymbol{H}$, with $\boldsymbol{H} = \boldsymbol{E}_{\text{a}}/\boldsymbol{w}$. The amounts of energy that are individually received fit into the specific energy and socioeconomic characterization of each consumer.

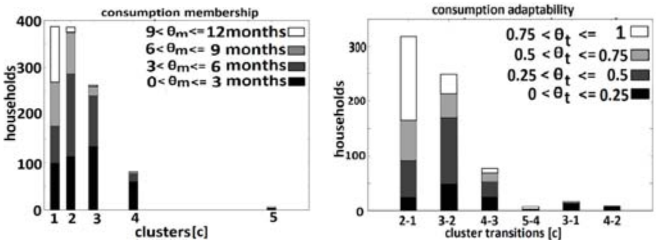
Water-Filling strategy (WF): At the beginning, different weights are given to each consumer by the CC depending on the priority policy that is followed. Then, being informed regarding the deficiency of each consumer, the CC defines their $\boldsymbol{H}$. However, in this EAS, the CC arranges the $\boldsymbol{H}$ 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. 2b. Let us assume that the transferred energy is added on top of the $\boldsymbol{H}$ of every consumer, as *additional service-level*, $\boldsymbol{h} = \boldsymbol{E}_{\text{g}}/\boldsymbol{w}$. 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 $H_l - H_j \geqslant H_j$, and thus the consumer j is fully covered before l starts requesting for energy. A number of consumers can be served simultaneously at any time instance, as long as they have equal sums of H and h (cf. Fig. 2b).

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 we 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?

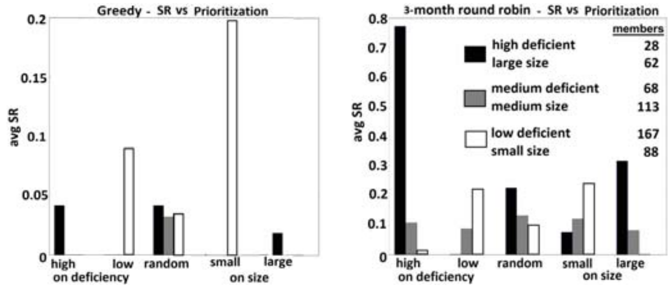
To quantify the potential of a strategy in covering completely the needs of (a group of) consumers c within a community, we define the *Served Ratio* (SR) metric for T as, SR $= \sum_{k=1}^{c} C_{\text{served},k}/c$. To evaluate the efficiency of prosumers in serving (a group of) consumers during T, we define the *Prosumers Beneficial Ratio* (PBR), PBR $= \sum_{k=1}^{c} C_{\text{notServed},k}/p$. 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 $T_a, T_b \in [1, T_{\text{max}}]$, UR $= \sum_{T=T_a}^{T_b} \sum_{k=1}^{c} C^{T}_{\text{unique},k}/c$.

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 ER$_k = E_{\text{g},k}/E_{\text{a},k}$. When 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 differently the community. Prioritized households are more important in terms of service and should receive higher



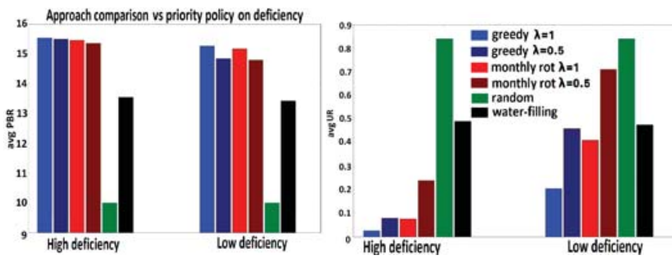
(a) Membership
(b) Adaptability

Fig. 3: Temporal energy behaviors



(a) Greedy
(b) Round-robin

Fig. 4: Average SR according to different priority policies



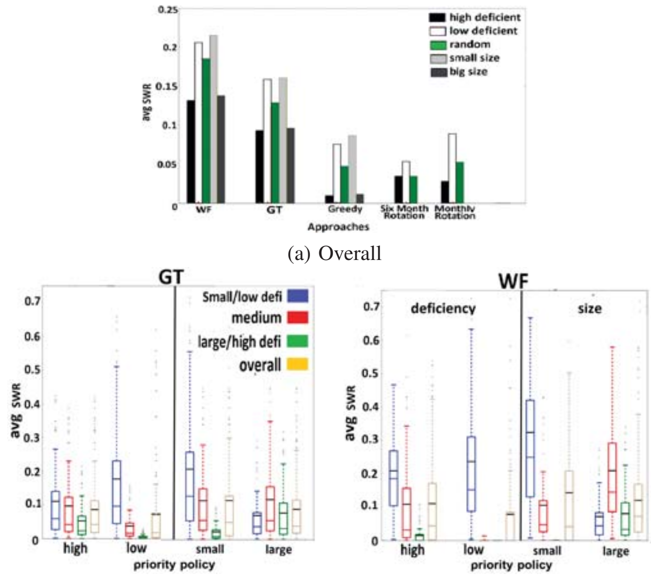
(a) PBR
(b) UR

Fig. 5: Prosumer usage – Service diversity (week 38-49)

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 $\log_2$ 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 $\mathrm{ER}_k = 1$, and 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, we have, $\mathrm{SWR}_c = \sum_{k=1}^{c} \log_2(1 + \mathrm{ER}_k)$.

VI. Implementation Results

We evaluate the temporal energy behavior of households using membership and adaptability. In Fig. 3a, 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. 3a, 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. In Fig. 3b, 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 energy regulation potential from the households. As shown in Fig. 3b, 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. 3a). In Fig. 4a and Fig. 4b, 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. 4b, 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. 5a and Fig. 5b, 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. 5b). Because of no priority in serving, the random approach has much lower PBR (Fig. 5a) and high diversity; serving almost 85% of the consumers (Fig. 5b). Service-fairness in a community is described by the SWR metric. In Fig. 6a, 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. Further, 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. The performance of the random policy stays between other policies, as it gives priority to none. 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. 6b and Fig. 6c, their impact on different groups of households (which have been assigned with the same priority



(a) Overall

(b) Game Theoretic (c) Water Filling

Fig. 6: Community social welfare ratio (yearly)

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. 6a. Further, the GT EAS is more stable than WF, because in WF we observe more outliers.

VII. Conclusion

With the growing adoption of renewable energy sources, consumers and prosumers are able to redistribute energy efficiently. ICT infrastructures provide communication needed between consumers and prosumers 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 paper, we proposed and evaluated six EASs that could be easily computed at the edge of SGs, which control the allocation of excess 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. Our approach is novel in the way we characterize an MG community. We clustered households into multiple groups thereby making it easy to analyze the complex behaviour 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 energy harvested 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. This work is one of the highly comprehensive studies of energy sharing in MGs of small consumers/prosumers. Expecting every household to be a prosumer in future it will be interesting to evaluate the scaling potential of our EASs in a system of distributed MGs.

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References

[1] E. Mengelkamp *et al.*, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Applied Energy*, 2018.
[2] I. S. Bayram and T. S. Ustun, "A survey on behind the meter energy management systems in smart grid," *Renewable and Sustainable Energy Reviews*, 2017.
[3] Y. Wang *et al.*, "Deep learning-based socio-demographic information identification from smart meter data," *IEEE Transactions on Smart Grid*, May 2019.
[4] N. Kouvelas, "Energy allocation strategies for Micro-grids," *MSc thesis, Delft University of Technology*, 2017.
[5] "Pecan Street," www.pecanstreet.org, [Online; accessed 25-Aug-2019].
[6] T. Morstyn *et al.*, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nature Energy*, 2018.
[7] C. Long *et al.*, "Peer-to-peer energy sharing through a two-stage aggregated battery control in a community microgrid," *Applied Energy*, 2018.
[8] T. AlSkaif *et al.*, "Reputation-based joint scheduling of households appliances and storage in a microgrid with a shared battery," *Energy and Buildings*, 2017.
[9] W. Shi *et al.*, "Real-Time Energy Management in Microgrids," *IEEE Transactions on Smart Grid*, Jan 2017.
[10] T. Liu *et al.*, "Energy management of cooperative microgrids: A distributed optimization approach," *International Journal of Electrical Power and Energy Systems*, 2018.
[11] W. Ma *et al.*, "Distributed energy management for networked microgrids using Online ADMM with Regret," *IEEE Transactions on Smart Grid*, March 2018.
[12] Y. Du *et al.*, "A cooperative game approach for coordinating multi-microgrid operation within distribution systems," *Applied Energy*, 2018.
[13] W. Tushar *et al.*, "A motivational game-theoretic approach for peer-to-peer energy trading in the smart grid," *Applied Energy*, 2019.
[14] A. U. Nambi *et al.*, "Temporal self regulation of energy demand," *IEEE Transactions on Industrial Informatics*, 2016.