C2C: Community-Based Cooperative Energy Consumption in Smart Grid

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***Abstract*—In this paper, a *community-based cooperative energy consumption* (*C2C*) scheme in smart grid, which alleviates energy consumption cost to customers, is proposed. The concept of community among customers in the smart grid is discussed. To form different communities among customers, a community-based game among customers is orchestrated, while considering the dynamic nature of the composition of the community. A practical scenario involving multiple customers forming a group and cooperating with one another is considered. The proposed dynamic community formation scheme always achieves an equilibrium state. Furthermore, the proposed scheme also helps to reduce *peak-to-average* ratio of the energy demands from the customers in different time periods. Simulation results show that the proposed cooperation-based scheme outperforms the existing schemes. It is also shown that customers can minimize their energy consumption cost by approximately 16% using the proposed scheme, compared to non-cooperative approaches.**

***Index Terms*—Community, Cooperation, Game Theory, Cooperation, Smart Grid**

NOMENCLATURE

$E^i_{req,t}$	Required energy of customer i at time t
$E^i_{com,t}$	Energy spent for communication at time t
$\mathcal{E}^i_{req}$	Required energy of customer i for a day
C^t_c	Unit energy cost
$v(S)$	Payoff value of a community
$\mathcal{U}_c$	Utility of customer
$\mathcal{S}$	Set of communities
$\psi_i(S)$	Preference of a community
$\Phi_i(v)$	Shapley value

I. INTRODUCTION

Unidirectional information collection and power flow poses different challenges to the traditional power grid to provide electricity to the customers in a cost-effective and reliable manner [1]. Therefore, the *smart grid* technology was introduced with an objective to provide electricity in a cost-effective and reliable manner with the help of bidirectional information collection and power flows. Towards this objective, different schemes such as dynamic pricing [2], demand scheduling [3], and distributed generation facilities [4] are proposed in the literature for improvement of service satisfaction and reduction of energy cost to the customers. Different schemes are also proposed at the micro-grid level for real-time energy management [5]–[7]. For example, an operational architecture for real-time energy management is proposed in islanded micro-grids [8], [9]. Consequently, real-time energy generation cost can be minimized significantly. Real-time pricing policy is also an important factor to be considered for utility maximization in smart grid. A scheme for the formulation of real-time pricing policy is proposed for which utility of the grid is maximized [2]. In such a study, an energy consumption controller is introduced to control the energy consumption at the customers' end, based on the real-time price decided by the grid. Additionally, real-time energy management schemes at micro-grids are also experimentally presented [10], [11]. It is observed that the energy consumption cost can be minimized in the presence of adequate energy management policies at both the grid and customer ends.

A game-theoretic energy consumption scheduling scheme is proposed for demand side management in a smart grid [12]. Using their scheme, the customers schedule their appliances by considering real-time price tariffs decided by the service provider. An appliance scheduling scheme for home energy management in the presence of wireless sensor networks is proposed by Erol-Kantarci and Mouftah [13]. However, the customers may incur more costs in a dynamic pricing scenario, while scheduling the appliances in different time periods. This is because the customers schedule their appliances in a non-cooperative manner. To address this problem, a dynamic demand scheduling scheme is proposed [3]. In such a scheme, the customers schedule their appliances dynamically, while considering the associated risk in the scheduling process. Subsequently, the authors showed that the customers can minimize their energy consumption cost significantly by scheduling the appliances dynamically, while considering the associated risks. An autonomous appliance scheduling scheme in the presence of non-dispatchable energy sources at the customers' end is proposed by Adika and Wang [14]. In their scheme, a smart decision is taken about the energy sources to be used (i.e., dispatchable or non-dispatchable). A multi-objective optimization approach for energy consumption scheduling is also introduced in smart grid to minimize energy consumption cost [15], [16].

The customers, however, schedule their appliances in different time periods in order to minimize their energy consumption cost. In such a scenario, it is possible that all the customers may schedule their appliances in a single time period, which, in turn, maximizes the total energy demand in that particular duration. Consequently, in a dynamic pricing scenario, the customers incur higher costs for energy consumption, though they schedule their own appliances. Additionally, the higher *peak-to-average* demand ratio causes an imbalance between the energy supply and demand at the service provider's end.

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Recently, few schemes [17], [18] for cooperation-based energy scheduling for customers were proposed. However, in these schemes, cooperation is either ensured in a centralized manner, or it is distributed at the grid-level. Therefore, in the existing scenarios, it is assumed that the entities are always willing to participate in the group formation. However, this assumption may not be always true for the community-based customers in real-life in a smart grid [19]. Additionally, the dynamic nature of communities needs to be taken into account, as the customers may have different interests in different time-periods.

In this paper, cost-effective energy consumption to the customers in the smart grid is investigated in a cooperative manner. The main contributions of the paper are as follows.

• A community-based cooperative energy consumption scheduling scheme, *C2C*, is proposed from a game-theoretic perspective. Instead of considering a common cooperative scenario, we propose a community-based cooperative smart grid architecture. A practical scenario is considered, in which the customers in a community help one another in order to minimize their energy consumption cost.

• *Cooperative game modeling* [20] is used to form communities among customers, while considering the dynamic nature of the community. It is, theoretically, shown that the proposed game model is *non-cohesive* in nature. The distributed algorithm consisting of strategies, whether to join a community or leave it for community formation, is also presented.

• Extensive simulation experiments are carried to show the effectiveness of the propose scheme over the existing 'non-cooperative' schemes. It is shown that the customers can minimize their energy consumption cost significantly, while fulfilling their energy requirements for a day.

The rest of the manuscript is organized as follows. Section III presents the detailed architecture of the proposed scheme. In Section IV, the proposed community-based cooperative energy consumption scheduling scheme is described in detail. Section V presents simulation results to show the effectiveness of the proposed scheme. The proposed scheme is discussed from the practical aspects in Section VI. Finally, Section VII concludes the manuscript with some future research directions.

II. The Concept of Community in Smart Grid

In smart grid, a micro-grid (small-scale power generation and distribution unit) provides electricity in a particular region. Within the service area of the micro-grid, different customers that can form different communities [21] among themselves according to their common interests of energy consumption, exist. Therefore, for a large-scale deployment of the smart grid, multiple communities can be formed with multiple micro-grids.

Customers are associated with two attributes — *energy demand* and *cost of energy*. The former is related to the customers' energy requirements. On the other hand, the latter is related to the real-time cost of energy that is to be paid by the customers for their energy consumption. Intuitively, the two issues of concern to customers are as follows:

• *Energy Reliability*: The customers in the smart grid are concerned about the consistency of energy service from the upstream grid. The customers check for the energy reliability before forming communities, i.e., how much reliable the community is to fulfill his/her requirements at the particular time period.

• *Energy Cost*: The cost of energy includes cost of energy consumption, and the communication cost to form communities among customers. Therefore, the cost of energy can vary with different deployment models of the smart grid. The customers always want to minimize their energy consumption cost, while fulfilling their energy requirements.

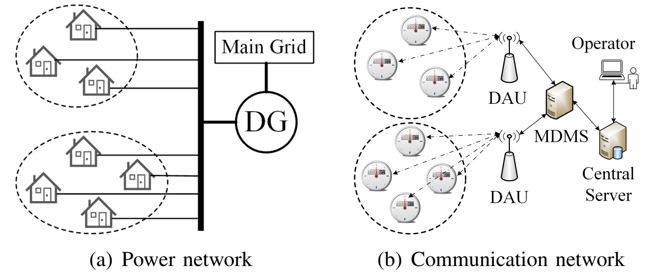


Fig. 1: Schematic diagram of a community-based smart grid

It is assumed that that the policy for evaluating real-time unit-energy cost is unique for all micro-grids. The quadratic cost function [22] is followed to decide the real-time energy cost of energy in a dynamic pricing scenario. Figure 1 depicts the community-based smart grid architecture considered in this work, where the customers form different communities among themselves. Customers communicate with the data aggregator units (DAUs) in order to exchange real-time information (such as energy demand and price) with the service provider. The DAUs act as relaying devices and the real-time information is sent to the meter data management systems (MDMS). According to the total energy demand from the customers, energy is supplied through the power distribution networks from the power generation unit.

III. System Model

The set of customers is represented by the set $\mathcal{C} = \{C_1, C_2, \ldots, C_N\}$, where N is the total number of customers. Additionally, it is assumed that the customers have different number of appliances[1]. Therefore, the set of appliances for a particular customer, $i \in [1, N]$, is represented as $\mathcal{A}_{C_i}$. The required energy by a customer, $i \in [1, N]$, may differ from another customer, $j \in [1, N]$, $i \neq j$. In such a scenario, the customers form different communities in order to consume energy in a cost-effective manner. Therefore, communities are to be formed considering allowable service delay, i.e., if the total demand from all the communities is greater than the total energy supply available to the grid, the energy demand in the community with higher allowable service delay is deferred to the next time period, while considering customers' participation.

[1]Two types of appliances are considered in this work — *shiftable* and *non-shiftable*. The shiftable appliances (such as fridge and washing machine) can be scheduled in any time period. On the other hand, the non-shiftable appliances (such as fan and light) cannot be scheduled in different time periods.

A. Objective of the Customers

It is considered that there are total T time periods in a day, which is represented as a set $\mathcal{T} = \{1, 2, \ldots, T\}$. Let the total demand of a customer, $i \in \mathcal{C}$, in a particular time period, $t \in \mathcal{T}$, be $E_{i,t}$. For the time period, $t \in \mathcal{T}$, the consumed energy at the customer-end is the combination of the required energy, $E_{req,t}$, for appliances and the energy for communication, $E_{com,t}$, with other customers for cooperation. In a cooperative scenario, customers communicate among themselves in order to take adequate decisions. Therefore, certain amount of energy is spent for communication. In smart grid, smart meters are used to exchange information between the customers and the grid. Moreover, the smart meters can communicate among themselves [1] to exchange information. Consequently, certain amount of energy is spent by the smart meters for taking decisions in a cooperative manner. We use the conventional energy consumption model for communication using the IEEE 802.11 protocol [23]. It is proportional to the number of packets to be transmitted in addition to a pre-determined energy consumption.

Therefore, the objective of the customers is to minimize their energy consumption cost, while fulfilling their energy requirements. Mathematically,

$$\text{Minimize} \quad \mathcal{C}_{\mathcal{T}} = \sum_{t=1}^{t=T} \left(\sum_{i=1}^{M} C_t^c \Big(E_{req,t}^i + \sum_{j \in \mathcal{N}, i \neq j} E_{com,t}^{ij} \Big) \right)$$

$$\text{subject to} \quad 0 \leq \sum_{i=1}^{M} E_{req,t}^i \geq 0, \text{ and } \sum_{t=1}^{T} E_{req,t}^i \leq \mathcal{E}_{req}^i \quad (1)$$

where M is the number of customers requested for energy in the time period t, and $M \leq N$. C_t^c is the unit energy cost offered by the upstream grid at time period t. In Equation (1), former constraint denotes that the total energy demand from the customers in a time period is always less than or equal to the total available supply to a balance between energy supply and demand, and is always greater than or equal to zero. The later is used to check whether the total consumed energy is equal to the required energy for the day. The customer consumes energy until his/her requirement is fulfilled.

B. Use of Community-Based Cooperative Game Theory

In a smart grid, several customers consume energy from a micro-grid (i.e., small-scale power grid consisting of dispatchable and non-dispatchable energy sources). Therefore, the customers serviced by a particular micro-grid are treated as a community. For large-scale deployment of a grid, several customers are serviced by multiple micro-grids, and form different communities. This situation is termed as *community-based* energy consumption.

Cooperative game theory [20] is one of the useful approaches to form communities among different players. The players join different communities for which their payoff values are maximized. Similarly, in the smart grid, the customers' objective is to minimize their energy consumption cost (which, in turn, maximizes their payoff values) by forming different communities, as discussed in Section I. In such a scenario, different strategies are defined for the customers to form communities. Thus, cooperative game theory is useful to form communities among customers, while considering the privacy policies. As the main objective is to form different communities to minimize energy consumption cost to the customer, for simplicity, security aspects of the customers are not considered in this work. Therefore, cooperative game theory for forming communities among customers is used in a smart grid. It is noteworthy that energy demand and cost are used to formulate utility function in the proposed scheme.

IV. Community-Based Energy Consumption

The concept of *cooperative* game theory [20] is used to form different communities among customers. The customers focus on their payoff values to be increased by forming a community of individuals. The community is denoted as $(\mathcal{N}, v)$, where $\mathcal{N}$ is the set of customers, represented as, $\mathcal{N} = \{1, 2, \ldots, N\}$. The payoff value received by the customers is denoted as v, while forming the community (or group) among themselves. In the subsequent section, some of the generic properties of the cooperative game are presented from different aspects of smart grid.

A. Properties of the Game

This typical game is defined by a pair $(\mathcal{N}, v)$, where $\mathcal{N}$ is a finite set of all customers, i.e., $\mathcal{N} = \{1, 2, \ldots, N\}$ and $v : 2^N \rightarrow \mathbb{R}$ is a function from a set of all possible communities $S \subseteq \mathcal{N}$ of the customers. The considered game model has a *characteristic form*, in which the utility of a community, $\mathbb{U}$, depends solely on the customers of that community and is independent on the way the customers in $\mathcal{N} \setminus \mathcal{S}$ are arranged. On the other hand, the game model has a *partition form*, in which the utility of the community, $\mathbb{U}$, depends on the arrangement of customers in $\mathcal{N} \setminus \mathcal{S}$. Therefore, the payoff, $v(\mathcal{S})$, of the community, $\mathcal{S}$, may or may not be distributed among its members, depending on *Transferable utility* (TU) property of the game.

Property 1. *The proposed game model $(\mathcal{N}, v)$ is a transferable utility (TU) game. The TU property implies that the payoff can be distributed in any manner among the customers of the community. The amount of utility that a customer $i \in \mathcal{S}$ receives from the distribution of $v(\mathcal{S})$ is called the payoff of the customer i, and it is denoted by Φ_i.*

Property 2. *In the proposed scheme, the community (N, v) with N customers always maintain a graph form.*

As discussed in Section III, a customer's energy consumption cost is the combination of cost of energy demand and cost of communication. Therefore, to form communities, it is necessary to consider the coordination chain, which defines the relationship among the customers.

Theorem 1. *The game $(\mathcal{N}, v)$ with TU is non-cohesive.*

Proof. The payoff of the whole community is at least as large as the summation of the individual payoffs of the partitions of the communities. Mathematically, $v(S) = \sum_{i=1}^{C} v(S_i)$, where S_i is the i^{th} community, and total C numbers of communities are formed from the set of customers $\mathcal{N}$. Therefore, the customers prefer to form communities among themselves, rather than consuming energy individually. However, the customers also calculate the cost involved in forming the communities among themselves. Therefore, the formation of a grand community may not be the optimal one with an increase in the cost of community formation. Intuitively, the proposed game model is non-cohesive in nature. □

Definition 1. *A collection $\mathcal{S} = \{S_1, S_2, ..., S_k\}$ is a group of mutually disjoint communities, $\mathcal{S}_i \subseteq \mathcal{N}$, which may or may not span over all the customers of $\mathcal{N}$. If the collection covers all the customers of $\mathcal{N}$, i.e. $\bigcup_{i=1}^{k} \mathcal{S}_i = \mathcal{N}$, then the collection is known as a partition $\prod$ of $\mathcal{N}$.*

Definition 2. *A preference order among two partitions, $\mathcal{P} = \{P_1, P_2, ..., P_m\}$ and $\mathcal{Q} = \{Q_1, Q_2, ..., Q_n\}$, $\mathcal{P}$ is preferred over $\mathcal{Q}$ if $\mathcal{P} \geq \mathcal{Q}$. Therefore, a customer, i, prefers collection $\mathcal{P}$ at-least as much as collection $\mathcal{Q}$, while given two collections $\mathcal{P}$ and $\mathcal{Q}$ and $\mathcal{P} \succeq_i \mathcal{Q}$. On the other hand, the customer i strictly prefers $\mathcal{P}$ over $\mathcal{Q}$, when $\mathcal{P} \succ_i \mathcal{Q}$.*

In the proposed scheme, each customer calculates his/her individual preference order and the community preference order, while consuming energy in an individual or community-based manner, respectively. Therefore, the preference order is categorized in two forms — *individual-value* and *community-value*. For example, in the *individual-value* preference order, *Pareto* order in which a collection $\mathcal{P}$ is preferred over a collection $\mathcal{Q}$ if at-least one customer's payoff increases with the collection $\mathcal{P}$ over the collection $\mathcal{Q}$ without decreasing payoff values of other customers. On the other hand, in *community-value* order, the preference of a collection is made based on the payoff value of the communities in the collection. Mathematically, $\mathcal{P} = \{P_1, P_2, ..., P_m\}$ is preferred over $\mathcal{Q} = \{Q_1, Q_2, ..., Q_n\}$ iff $\sum_{i=1}^{m} \mathcal{P}_i \geq \sum_{i=1}^{n} \mathcal{Q}_i$.

B. Utility of the Customers

One of the objectives of the customers is to consume the required energy, while considering the corresponding energy cost and energy requirements. Therefore, the utility function with energy demand increase with an increase in the energy demand, while energy cost and communication cost are constant to the customers. Mathematically, $\partial \mathcal{U}_c \left(E^i_{req,t}, C^c_t, E^{ij}_{com,t}\right) / \partial E^i_{req,t} > 0$. In contrast, the utility of the customers is a decreasing function with real-time energy cost, C^c_t. Mathematically, $\partial \mathcal{U}_c \left(E^i_{req,t}, C^c_t, E^{ij}_{com,t}\right) / \partial C^c_t < 0$. This defines that the customers' utility decreases with an increase in the energy consumption cost, while other parameters remain constant. Therefore, the customers always prefer to consume energy with lower energy cost. Similarly, a decreasing function of the utility is present with the communication cost, $D^{ij}_{com,t}$. Mathematically, $\partial \mathcal{U}_c \left(E^i_{req,t}, C^c_t, E^{ij}_{com,t}\right) / \partial E^{ij}_{com,t} < 0$. After combining all the Equations, the obtained utility function of the customer is as follows:

$$\mathcal{U}_c = k\left(E^i_{req,t} - \beta \sum_{j \in N j \neq i} \left(E^{ij}_{com,t}\right)^2\right)\left(\frac{1}{C^c_t} - \frac{1}{C^c_{max,t}}\right) \quad (2)$$

where β is a predefined constant which signifies the effect of distance in the utility function, and k is the proportionality constant. $C^c_{max,t}$ is the maximum unit energy cost in the time period t offered by the grid. Therefore, from Equation (2), it is evident that the utility of the customers increases with decrease in the real-time unit energy cost, C^c_t. The utility also decreases with an increase in the communication cost. Therefore, the utility function presented in Equation (2) follows all the properties mentioned above. Hence, we get the total payoff in a community according to the utility.

As the proposed model is the transferable utility game (as mentioned in Property 1), the *Egalitarian property* [24] is considered to calculate the distribution of payoff in a community. Mathematically, the *Egalitarian property*-based utility division is presented as follows:

$$x_i(S) = \frac{1}{|S|} v(S) - \sum_{j \in S} v\big(\{j\}\big) + v(\{i\}) \quad (3)$$

where $x_i(S)$ is the payoff of the player $i \in S$ where $S \subseteq \mathcal{N}$. The individual payoff $x_i(S)$ for a player i depends on shared payoff $v(\{i\})$, in addition to the total payoff in the community. We use the energy demand and its flexibility rate to calculate the shared payoff of a customer, which is similar to the scheme proposed by Baharlouei et al. [25]. Therefore, the fairness among the customers is also ensured, as the shared payoff depends on the energy demand and appliance flexibility rate.

C. Preference Order Selection

In the proposed scheme, the preference order is considered as the function of the utility of the individual customers in a community, as the customers always want to maximize their own payoff (as discussed in Section I). Therefore, a customer joins a community if and only if his/her individual utility increases by joining that community. Similarly, the customer may also leave a community depending on the changes in his/her utility. Therefore, the *individual-value* preference order rule is used to compare payoff values with two or more collections over the same set of customers. Mathematically, $S_1 \succeq_i S_2 \Leftrightarrow \psi_i(S_1) \geqslant \psi(S_2)$, where $\psi_i(S_i)$ is the preference function, and is represented as follows:

$$\psi_i(S) = \begin{cases} v_i(S), & \text{if } S \notin h(i) \\ -\infty, & \text{otherwise} \end{cases} \quad (4)$$

where $v_i(S)$ is the shared payoff of customer, i, from the the total payoff of community, S, $h(i)$ is a history set of communities to which the customer, i, joined previously. Therefore, a rule is defined that a customer cannot rejoin a community in which he/she joined earlier in the same time period.

D. Equilibrium Strategy of the Proposed Scheme

The proposed scheme consists of several iterations. In every iteration, a customer checks his/her own utility, while considering others' strategies. According to the utility, the customer joins/leaves to/from a community. Finally, it is desired to have an equilibrium strategy in which the utility of the customer is saturated. Consequently, after forming different communities among customers, it is necessary to have a stable scenario among them. Therefore, there exists a condition where a customer, i, cannot improve his/her utility by joining/splitting to/from a community. It is noteworthy that multiple equilibrium points can exist for which the utility of the customers is maximized. Therefore, an equilibrium point based on selecting argument of the maximum is selected. Mathematically, the equilibrium condition is represented as follows:

$$\mathcal{U}_{c,i}\big(S_i, E^i_{req}, C^c_t, E^{ij}_{com,t}\big) \geq \mathcal{U}^*_{c,i}\big(S^*_i, E^i_{req}, C^c_t, E^{ij}_{com,t}\big) \quad (5)$$

where $\mathcal{U}^*_{c,i}$ is the payoff value obtained by the customer, i, by joining a new community $\mathcal{S}^*_i$.

On the other hand, a partition, π, is said to be *individually stable*, if there does not exist a customer, i, and a community, S_k, such that the customer prefers to join S_k, instead of being in the present community in the current partition. Therefore, if $\pi = \{S_1, S_2, \ldots, S_l\}$ is stable, the following criteria are always applicable: $\cup\{\phi\} : \neg\big(S_k \cup \{i\} \succeq_i S_\pi(i)$ && $S_k \cup \{i\} \succeq_j S_k\big), \forall j \in S_k, \forall i \in \mathcal{N}, \forall S_k \in \pi$.

Theorem 2. *Using the proposed scheme, a stable condition, Π_f, always exists among communities.*

Proof. Firstly, the maximum number of partitions is calculated, among N number of customers, using the Bell number function [26]. Mathematically,

$$\mathcal{B}_N = \sum_{i=1}^{N} \binom{N-1}{i} \mathcal{B}_i, \text{ for } i \geq 1 \text{ and } \mathcal{B}_0 = 1 \quad (6)$$

where $\mathcal{B}_N$ is the number of possible partitions with N customers. Therefore, the number of communities that can be formed with N number of customers is also finite. Let us consider that a customer, i, joins a community, $S_{k,t}$, at time, t, in which he/she did not join before, while there is a partition transformation from π_t to π_{t+1}. Therefore, a new community, $S_{k,t} \cup \{i\}$, is present. Otherwise, the old community as $\{i\}$ exists, where other customers may or may not be there. Thus, this strategy leads to form new communities in every transformation. However, according to Equation (6), as there are finite number of partitions, the customer, i, has limited options to join a new community, $S_{k,t+1}$, or to remain the present community. Intuitively, the number of transformations is also limited, which, in turn, establishes a stable partition, Π_f. □

For simplicity, it is considered that the unit energy cost offered by the grid in the stable state of the communities does not change in real-time. Therefore, the uncertainty issues are not focused in this paper. Moreover, it is also considered that the customers cooperate with one another in a community. Therefore, the real-time unit energy cost is not changed for a community from the offered one.

E. Proposed Algorithm

The proposed algorithm for community-based cooperative energy consumption scheme, C2C, is presented in Algorithm 1. The proposed algorithm consists of two mechanisms — *joining* a community and *splitting* it. Therefore, firstly, the steps for joining or leaving a community from a customer's viewpoint are presented. Secondly, the steps for the merging of two communities, or a sub-community leaving a community are presented. In a particular time period, communities are formed among customers according to their mutual decisions and appliance flexibility rates for which utilities of the customers are maximized. Consequently, the dynamic nature of the community takes effect until a stable condition is achieved in which all customers in a particular community agree with a decision (please refer to Figure 4(b)). It is noteworthy that the stable condition is achieved after several iterations consisting of joining or leaving a community. In the community formation process, a customer forms a community initially when other communities do not exist. In other words, either any other community does not exist or existing communities do not fulfill the community formation rules, while including the current customer. Consequently, the customer who forms the community acts as a leader in that community. Hence, the customer provides information about the community to the other customers willing to join the community. We limit the total energy demand from the customers for a community. Therefore, for a community, once total energy is equivalent to the allowable energy demand, no more customers can be added into that community, although the utility of the customers increases by adding the new customers. Time complexity for joining a community is O(n). On the other hand, to leave an existing community, the time complexity is O(1). Therefore, the total time complexity of the proposed scheme is O(n+1), i.e., O(n).

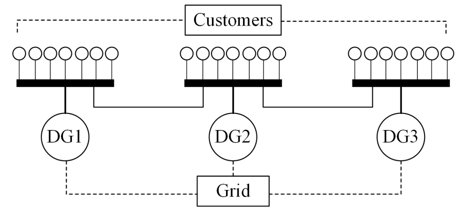


Fig. 2: A single line diagram of the simulation

V. Performance Evaluation

In this Section, the performance of the proposed scheme, C2C, is evaluated using MATLAB. Different number of customers are considered as 50 – 500. Therefore, both the small- and large-scale smart grid architecture is considered. Energy demand of a customer is considered as 10 – 20 kWh [27]. For simplicity, a total of 24 time periods in the simulation is considered. However, the number of total time periods can be considered according to the user's choice. The load flexibility rate is considered as $10 - 100\%$. For each customer, it is assumed that $10 - 100\%$ of current energy demand can be shifted to next time periods. The exact value for simulation is chosen in a random manner for each customer. For this reason, cumulative average is also taken, to get unbiased results. Additionally, the confidence interval is included to show the confidence level. Figure 2 shows a single line diagram (SLD) of the simulation. Nonlinear constrained optimization method

Algorithm 1: Algorithm for Community Formation

Input: Number of customers: N; Set of communities: $\mathcal{S}$;
Current community partition: π
Output: Stable communities with customers

For customer *i*;
Calculate utility, $\mathcal{U}_i\{\mathcal{S}_j\}$, for each community, $\mathcal{S}_j$, $j \in \mathcal{S}$;
Select a community $\mathcal{S}_k$ for which $\mathcal{U}_i\{\mathcal{S}_k\} > \mathcal{U}_i\{\mathcal{S}_l\}$ (if the customer i belongs to community $\mathcal{S}_l$) or $\mathcal{U}_i\{\mathcal{S}_k\} > \mathcal{U}_i\{i\}$ (if the customer i does not belong to any community), $\mathcal{S}_k \neq \mathcal{S}_l$;
Send join request to $\mathcal{S}_k$;
Receive acknowledgement from $\mathcal{S}_k$;
Send leave request to $\mathcal{S}_l$, and receive ACK;
Join the community $\mathcal{S}_k$;

For community $\mathcal{S}_k$;
Receive join request from a customer i or a community $\mathcal{S}_l$;
Calculate $\mathbb{U}\{\mathcal{S}_m\}$, $\mathcal{S}_m = \mathcal{S}_k \cup \mathcal{S}_l$ or $\mathcal{S}_m = \mathcal{S}_k \cup \{i\}$;
if $\mathbb{U}\{\mathcal{S}_m\} > \mathbb{U}\{\mathcal{S}_k\}$ **then**
  Approve join request from i or $\mathcal{S}_l$;
  Send acknowledgement to join;
  New community is formed;
else
  Send reject information to i or $\mathcal{S}_l$;
Receive leave request from i or $\mathcal{S}_l$, and send ACK;
Update: $\mathcal{S}_k = \mathcal{S}_k \setminus \{i\}$ or $\mathcal{S}_k = \mathcal{S}_k \setminus \{\mathcal{S}_l\}$;

in MATLAB is used to solve the optimization problem in each iteration.

The performance of the proposed scheme, C2C, is compared with the existing 'non-cooperative' schemes. Accordingly, the results for "non-cooperative" (NC) and *C2C* (proposed) schemes are presented. In NC, the customers schedule their appliances according to their own appliance flexibility rates and required energy demand without any knowledge about others. Therefore, the customers consume energy in a non-cooperative manner. The same values of different simulation parameters are considered for NC in performance evaluation. The only difference is that using the proposed scheme, C2C, customers consume energy in a cooperative manner, while having knowledge about others. On the other hand, in NC, the customers consume energy in a non-cooperative manner. It is also noteworthy that each customer consumes the same amount of energy using both the NC and C2C schemes to fulfill his/her energy requirement.

A. Results and Discussion

The effectiveness of the proposed scheme in terms of performance is shown in Sections V-A1 – V-A6.

1) Real-time Energy Demand: Real-time energy demand is the measure of the amount of energy requested to grid from the customers in different time periods. Therefore, the real-time energy demand is calculated in two respects – energy demand in (a) a *non-cooperative scenario*, and (b) a *cooperative scenario*. As discussed in Section I, if most of the customers send their energy demand in a single time period, the corresponding time period is treated as the peak period. Therefore, the real-time energy demand in different time periods is captured to show the effectiveness of the proposed scheme. Figure 3 shows the energy demand received by the grid from customers in different time periods. It can be seen that the requested energy demand from the customers is always moderate using the proposed scheme, C2C. This is attributed to cooperation

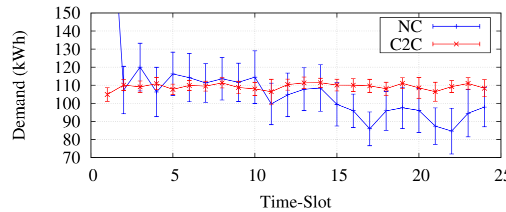


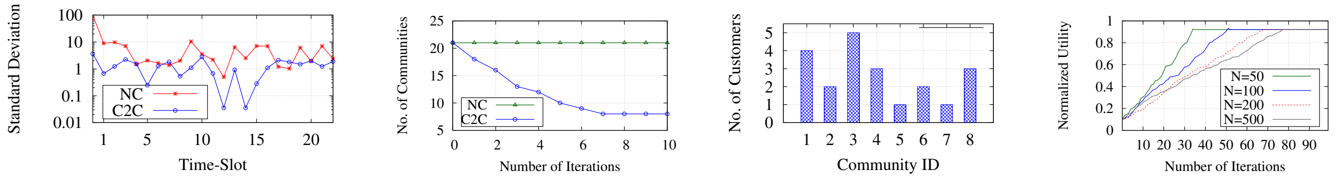
Fig. 3: Energy demand requested in different time-slots

among customers in different communities. Additionally, the shiftable energy demand from the customers is also shifted to the next time periods to minimize the peak-to-average ratio. As there is always a limit for maximum energy consumption for a particular community, additional demands are deferred to next time periods, while considering the appliance flexibility rates. In the NC-based situation, the demand requests are served instantaneously by the grid. However, in the absence of the cooperative nature of the customers, there is irregularity in the total energy demand requested by all the customers, which, in turn, creates heavy load on the grid. Intuitively, it can be said that using the proposed scheme, C2C, the *peak-to-average ratio*[2] to the grid can be minimized, which, thereby, establishes reliable energy service to the customers. It is noteworthy that in both the approaches, the customers consume the same amount of energy to fulfill their energy requirements.

2) Demand Variation: The demand variation is calculated according to the mean demand variation from one time period to the next time period. The mean value of the energy demand for one time period from a day-ahead energy graph is taken, and the demand variation in the form of standard deviation in different time periods throughout a day is calculated. Figure 4(a) shows the variation of total energy demand between different time periods from all customers present in different communities. It is observed that the demand variation is lower using the proposed scheme than using the existing scheme, while the customers form communities among themselves and act in a cooperative manner. The high demand variation may also create peak hours in different time periods. Therefore, it is shown that the demand variation can be minimized using the proposed scheme, while customers act in a community-based manner.

3) A Simple View of Community Formation: A simple view of community formation is presented in Figure 4(b), in which 21 customers have energy demands in a particular time-slot. Prior to the execution of the optimization process, 21 communities are formed among the customers. However, with an

[2]Peak-to-average ratio is the measure of deviation of energy demand from the average demand in a time period throughout a day.



(a) Standard deviation of energy demand (b) Dynamic change in communities (c) Customers in communities (d) Convergence of communities

Fig. 4: Results for demand variation, community formation, and convergence of communities

increase in the number of iterations, customers join an existing community, which, in turn, minimizes the total number of communities. Finally, after the optimization process, we see that 8 communities are formed among the customers. It is noteworthy that the size of the community depends on the total energy demand from the customers and the total utility of the community, as presented in Figure 4(c). In the proposed scheme, the customers form different communities among themselves, which are again dynamic in nature. In a dynamic pricing scenario of a smart grid, the unit energy consumption cost to customers varies depending on the demand and supply to the upstream grid. Therefore, based on the received dynamic price, the customers join/split into/from a community for which the energy consumption cost is minimized. Therefore, the number of formed communities also changes over time. This is referred to as the 'dynamic nature of a community', i.e., the size of a community changes over time. So, the dynamic nature of a community can be considered as a result of dynamic pricing in the proposed scheme.

4) Convergence of the Community: Figure 4(d) shows the convergence scenario of the formed communities with different number of customers. After multiple iterative steps, the utility of customers converges to a maximum value. It is shown that for less number of customers, it takes less number of steps to converge, as all customers enter into the system quickly. On the other hand, it takes more number of steps to converge for large number of customers. Therefore, as mentioned in Section IV-D, an equilibrium state exists after several iterative steps.

5) Energy Cost to Customers: Figure 5(a) shows the total energy consumption cost to the customers. In a dynamic pricing scenario, using the proposed approach, the customers consume energy in a cooperative manner, so that the real-time energy consumption cost to the customers is minimized, as presented in Section III. It is seen that the customers incur less amount of energy consumption cost using the proposed scheme. On the other hand, they incur increased cost, if they do not consume energy in a cooperative manner by forming communities. In the proposed scheme, the customers defer their energy demands to next time periods considering the appliance flexibility rates. Therefore, in a dynamic pricing scenario, the market clearing price is less using the proposed approach, compared to the non-cooperative approaches. Consequently, the energy consumption cost to the customers is minimized using the proposed scheme over the existing non-cooperative approaches.

The total energy consumption cost with different number of customers is also presented. In Figure 5(b), the cumulative energy consumption cost to the customers is plotted against the number of customers with the proposed scheme, C2C, and the NC scheme. From the Figure, it may be inferred that for any number of customers, the energy consumption cost reduces when they are grouped into communities. It is shown that the proposed approach outperforms the NC-based schemes with varying number of customers as well.

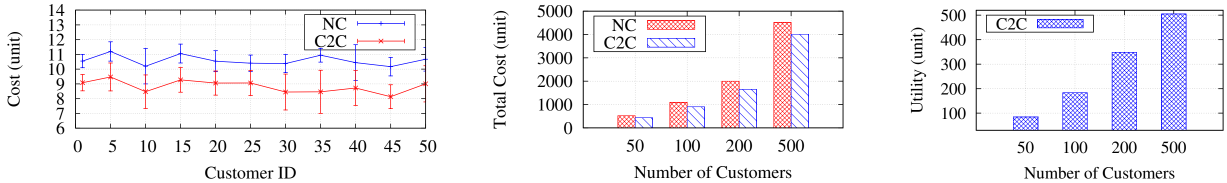
6) Utility of Customers: After calculating the energy consumption cost to the customers, the utility to individual customers and the total utility with different number of customers is calculated. Figure 5(c) shows the increase in total utility to the customers over the "non-cooperative" case. It is evident that the utility of the customers increases approximately 16% over the existing one. Thus, it may be inferred that with varying number of customers, the proposed scheme outperforms the existing one in terms of the total utility, when the customers adopt the community-based energy consumption technique.

VI. Discussion: Practical Perspective

In this Section, different applications of the proposed scheme, C2C, are discussed briefly from the practical perspectives. The main objective of the customers in a smart grid is to minimize the energy consumption cost, while fulfilling the required energy requirement. Therefore, the primary objective of the proposed scheme is to minimize the energy consumption cost to the customers. In a practical scenario, different customers may have different appliance flexibility rates. Accordingly, the customers schedule their appliances in different time periods [3], [13]. Therefore, the idea is to schedule the appliances in a cooperative manner to minimize peak energy demand to the upstream grid, while having mutual decisions among customers. Hence, the proposed scheme helps customers to form different communities with mutual decisions to minimize the peak energy demand. As a result, the energy consumption cost is minimized, which is reflected in the simulation results. Consequently, in a practical scenario, C2C is capable of minimizing the energy consumption cost to customers, while fulfilling their energy requirements. Therefore, it is evident that the proposed scheme, C2C, is useful in the practical applications in a smart grid.

VII. Conclusion

In this paper, a community-based cooperative energy consumption scheme in smart grid was proposed with an aim to minimize the energy consumption cost to customers. Cooperative game-theoretic approach was used to form communities among customers. Simulation-based results showed that the



(a) Energy consumption cost with 50 customers (b) Total energy consumption cost (c) Total utility increases to the customers

Fig. 5: Energy consumption cost and utility to the customers

proposed approach, C2C, outperforms the existing ones in terms of energy cost minimization. The proposed scheme is also useful to reduce the *peak-to-average* ratio in the smart grid, so that reliable energy service can be provided to the customers.

In the proposed scheme, the customers share their own energy consumption information to others, and take coordinated decisions to minimize energy consumption cost. As a result, the chances of high energy price at a specific time period occurring are very less, compared to the same with non-cooperative one. However, the customers' privacy and security policies are a few issues of concern in case of the cooperative one. A *belief factor* may be introduced to form communities among customers. In that case, the customers will form communities among themselves depending on the belief factor, while considering the other factors such as energy demand, utility, and appliance flexibility rate.

REFERENCES

[1] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid The New and Improved Power Grid: A Survey," *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 944–980, 2012.

[2] P. Samadi, A. H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, "Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart Grid," in *Proc. of the IEEE SmartGridComm*, 2010, pp. 415–420.

[3] S. Bera, P. Gupta, and S. Misra, "D2S: Dynamic Demand Scheduling in Smart Grid Using Optimal Portfolio Selection Strategy," *IEEE Trans. on Smart Grid*, vol. 6, no. 3, pp. 1434–1442, 2015.

[4] Y. Wu, V. K. N. Lau, D. H. K. Tsang, L. P. Qian, and L. Meng, "Optimal Energy Scheduling for Residential Smart Grid with Centralized Renewable Energy Source," *IEEE Systems Journal*, vol. 8, no. 2, pp. 562–576, 2014.

[5] M. Marzband, N. Parhizi, M. Savaghebi, and J. M. Guerrero, "Distributed Smart Decision-Making for a Multimicrogrid System Based on a Hierarchical Interactive Architecture," *IEEE Trans. on Energy Conversion*, 2015, DOI: 10.1109/TEC.2015.2505358.

[6] M. Marzband, F. Azarinejadian, M. Savaghebi, and J. M. Guerrero, "An Optimal Energy Management System for Islanded Microgrids Based on Multiperiod Artificial Bee Colony Combined With Markov Chain," *IEEE Systems Journal*, 2015, DOI: 10.1109/JSYST.2015.2422253.

[7] M. Marzband, E. Yousefnejad, A. Sumper, and J. L. Domnguez-Garca, "Real time experimental implementation of optimum energy management system in standalone Microgrid by using multi-layer ant colony optimization," *International Journal of Electrical Power & Energy Systems (Elsevier)*, vol. 75, pp. 265–274, 2016.

[8] M. Marzband, A. Sumper, A. Ruiz-lvarez, J. L. Domnguez-Garca, and B. Tomoiaga, "Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets," *Applied Energy*, vol. 106, pp. 365–376, 2013.

[9] M. Marzband, A. S. andJos Luis Domnguez-Garca, and R. Gumara-Ferret, "Experimental Validation of a Real Time Energy Management System for Microgrids in Islanded Mode Using a Local Day-Ahead Electricity Market and MINLP," *Energy Conversion and Management*, vol. 76, pp. 314–322, 2013.

[10] M. Marzband, M. Ghadimi, A. Sumper, and J. L. Domnguez-Garca, "Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for microgrids in islanded mode," *Applied Energy*, vol. 128, pp. 164–174, 2014.

[11] M. Marzband, N. Parhizi, and J. Adabi, "Optimal energy management for stand-alone microgrids based on multi-period imperialist competition algorithm considering uncertainties: experimental validation," *International Transactions on Electrical Energy Systems*, 2015.

[12] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid," *IEEE Trans. on Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010.

[13] M. Erol-Kantarci and H. T. Mouftah, "Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid," *IEEE Trans. on Smart Grid*, vol. 2, no. 2, pp. 314 – 325, 2011.

[14] C. O. Adika and L. Wang, "Autonomous Appliance Scheduling for Household Energy Management," *IEEE Trans. on Smart Grid*, vol. 5, no. 2, pp. 673–682, 2014.

[15] H. Lu, M. Zhang, Z. Fei, and K. Mao, "Multi-Objective Energy Consumption Scheduling in Smart Grid Based on Tchebycheff Decomposition," *IEEE Trans. on Smart Grid*, vol. 6, no. 6, pp. 2869–2883, 2015.

[16] ——, "Multi-objective energy consumption scheduling based on decomposition algorithm with the non-uniform weight vector," *Applied Soft Computing*, vol. 39, pp. 223–239, 2016.

[17] S. Caron and G. Kesidis, "Incentive-Based Energy Consumption Scheduling Algorithms for the Smart Grid," in *Proc. of the IEEE SmartGridComm*, 2010, pp. 391–396.

[18] S. Salinas, M. Li, and P. Li, "Multi-Objective Optimal Energy Consumption Scheduling in Smart Grids," *IEEE Trans. on Smart Grid*, vol. 4, no. 1, pp. 341–348, 2012.

[19] "Voices of Experience: Insights of Smart Grid Customer Engagement," U.S. Department of Energy, Tech. Rep.

[20] P. Shenoy and Lawrence, "On Coalition Formation: A Game-Theoretical Approach," *Intl. Journal of Game Theory*, vol. 8, no. 3, pp. 133–164, 1979.

[21] D. Niyato and P. Wang, "Cooperative Transmission for Meter Data Collection in Smart Grid," *IEEE Communications Magazine*, vol. 50, no. 4, pp. 90–97, 2012.

[22] J. J. Grainger, *Power System Analysis*. NY, USA: McGraw-Hill Education, 2003.

[23] L. Feeney and M. Nilsson, "Investigating the energy consumption of a wireless network interface in an ad hoc networking environment," in *Proc. of the IEEE INFOCOM*, 2001.

[24] B. Dutta, "The egalitarian solution and reduced game properties in convex games," *International Journal of Game Theory*, vol. 19, no. 2, pp. 153–169, 1990.

[25] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad, "Achieving Optimality and Fairness in Autonomous Demand Response: Benchmarks and Billing Mechanisms," *IEEE Trans. on Smart Grid*, vol. 4, no. 2, pp. 968–975, 2013.

[26] T. Arnold and U. Schwalbe, "Dynamic coalition formation and the core," *J. of Economic Behavior & Organization*, vol. 49, pp. 363–380, 2002.

[27] [Online]. Available: http://www.eia.gov/electricity/sales_revenue_price/