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ORIGINAL ARTICLE

Game Theory Approach for Energy Consumption Scheduling of a Community of Smart Grids

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Abstract

This study analyzes the potential of an independent method of dynamic pricing schemes to reduce the peak demand in the neighborhood area. For this, this work develops a collective energy consumption scheduling (CECS) algorithm in the residential sector based on a combination of energy consumption plans under a bi-level game theory method. The local level is responsible of gathering internal users' data and reducing the energy consumption in each residential building. The central level is the external demand management system that is focused on modeling a coalition between the local load management modules, as well as giving the redistributed demand profile to increase the global profit through a peak load minimization, financial gain and peak-to-average-ratio reduction. Four controllable appliances are included in load shifting and time activation cycling: clothes dryer units, heating, ventilation and air conditioning systems, electric water heater, and electric vehicle. The principle of the proposed CECS method relies on the flexibility of the user requirement that presents one of the contributions of this study. It proposes a novel framework for determining optimal non-static load management strategies, in which consumers can change their daily power demand patterns depending on their routines, preferences and requirements. Numerical results show that time-varying schemes encourage customers to condense their electricity consumption within low-price periods. However, by incorporating the proposed approach of coordinated scheduling algorithm significant profits in the whole and single level are demonstrated. Simulations infer that given the same load profiles, the proposed framework outperforms the non-coordinated strategy leading to important rates in total peak load minimization, total saving in electricity bills and reduction of peak-to-average-ratio.

Keywords Smart grid · Rebound peak · Demand side management · Load shifting · Game theory

List of Symbols

Parameters

t	Time slot, $t \in \{0, \ldots, 24\}$
α	Considered device, $\alpha \in \{HVAC, CD, EV, EWH\}$
θ_t	The room temperature at each minute t, (°F)
G_i	The heat gain rate in the house at time slot t
Δc	The energy needed to change the room by 1°F in (Btu/°F)
C_{HVAC}	AC unit capacity, that takes positive value for heating and negative for cooling in $\left(\mathrm{Btu}/^{\circ}\mathrm{F}\right)$
P_{HVAC}	Rated power for space cooling (kW)
θ_{EWH}	The hot water temperature (°F)
$\Delta\theta_{EWH}$	Lower tolerance (°F)
θ_{inlet}	Inlet water temperature (°F)
θ_a	Ambient temperature in (°F)
fr_t	Hot water flow rate at time slot t in (gmp)
$A_{\tan k}$	The surface area of the tank $\left(\mathrm{ft}^2\right)$
$V_{\tan k}$	Volume of the tank $\left(\mathrm{ft}^3\right)$
$R_{\tan k}$	The heat resistance of the tank (°F ft^2 h/Btu)
Δt	Time duration in (h)
P_{EWH}	Rated power of the water heater (kW)
$t_{start}(CD)$	The required start time of CD operation
$t_{required}$	The drying operation duration (set to 90 min in this case)
k	Drying level in this case it is equal to 1/5
P_{CD}	Rated power of the Clothes Dryer (kW)
P_m	The power consumption of the motor (kW)
P_{EV}	The rated power for EV (kW)
$SoC_{\max}$	The maximum charge state of the battery
SoC_t	The state of charge of the battery at time t

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SoC_{t-1} The state of charge of the battery at time $t-1$
$D_{\alpha,t}$ Decision variable of device at time t

1 Introduction

1.1 Motivation

The modernization of the traditional power grid has resulted in the redesign of a new smart grid, highly reliable and fully automated. This smart grid fostered the integration of renewable sources, allowed both communication channels of supply and smart devices and communication devices, smart sensors and digital sensing for ongoing demand management [1]. Recently, the residential sector represents a high energy consumption area with about 40% of the world's energy demand [2]. Indeed, a major interest should be accorded to efficient home energy management (HEM) systems, targeting: (i) minimizing the overall cost, (ii) maximizing renewable energy sales, (iii) scheduling household appliances [3, 4], etc. To tackle these challenges introduced by smart grid management, two essential mechanisms are used to improve its energy efficiency. The first one is conducted by integrating alternative power resources instead of conventional to address the power generation side, especially in renewable power generation monitoring (solar, wind, hydro…). Throughout the concept, self-generation of electricity occurs when the user becomes a prosumer for the purpose of selling excess power to the grid or recharging local batteries [5]. Whereas the other mechanism deals with energy demand management by directly affecting load management activities [6]. In the demand side management (DSM) perspective, researchers are particularly interested in shifting loads to off-peak energy period [7], or monitoring the thermal characteristic of some appliances to avoid high energy consumption [8]. This is usually used to achieve a minimum energy cost or a maximum user convenience factor. Therefore, a careful design of the DSM program should enhance the potential of end-users in terms of electricity consumption.

Demand Response (DR) is a component of DSM approaches, designed to address end-user incentives based on market prices [9]. It provides a variety of operational and economic benefits to both electricity utility service and consumers [10]. The DR generally schedules controllable appliances in response to the time-varying price schemes, such as time-of-use (ToU) pricing, and real-time pricing (RTP) [11]. Indeed, the energy management system turns on the flexible loads after rush periods (starting of o_-peak times) to achieve the peak load reduction for power grids and economic profits improvement as to insure user's preferences. That may cause the accumulation of controllable load appliances at low-cost times. In this regard, it is required to develop a load scheduling model while considering various operation modes (user's references, owned appliances) to reduce the peak load. In this research work, we aim to investigate the capacity of an optimal non-static load management strategies, in which consumers can change their daily power demand patterns depending on their routines, preferences and requirements, such a novel contribution support our present work.

1.2 Related Works

By and large, dynamic pricing is mostly investigated in the HEM system using ToU and RTP schemes to save money. ToU pricing presents a lower cost volatility than the RTP signal [11]. Thus, ToU pricing is more adopted for residential users than RTP. In ToU scheme, the energy cost is determined day-ahead or at the beginning of a season. In Ref. [12], a HEM model for a residential user is presented in the purpose of minimizing electricity bill and peak costs. This scheduling method is based on ToU and inclined block rate (IBR) pricing schemes. The appliances categorization and priority factors are also incorporated in DR program. Despite the maximization of user comfort and minimization of energy cost, the Peak-to-Average Ratio (PAR) has not been considered. An interval number optimization method is used in [13] for load scheduling. Appliances are divided into: non-interruptible, interruptible and thermostatically interruptible. Combined Binary Particle Swarm Optimization (BPSO) with integer linear programming (ILP) are considered to handle the problem of electricity cost minimization. A profit of 3% reduction in the total cost is achieved. The involvement of ToU pricing for home power scheduling technique has been also investigated in [14–16]. Furthermore, selfish HEM systems are not often a profit. For example, if all consumers shift their loads to the lowest energy price periods, an overloading in the power grid, blackouts and rebound peaks could be occurred. Consequently, a collaborative combination of energy goals at neighbors scale is a vital crucial.

When several houses behave differently and participate in the same DR service in order to minimize high electricity cost or the total load demand, a potential should be developed for monitoring and optimizing different scenarios for energy schedules. An improved collective algorithm was proposed in [17] as an incentive for energy users to adopt system management schedules. The approach considers two types of home units: power shifftable which have an adaptive power to answer variations of the required scheduling such as air conditioner and water heater, and time shifftable units that can be shifted to a predetermined time interval. The experimental results show that in addition to saving 15.6% of energy use and production costs, a game theory must be studied for the programming model. Study [18] was designed to simultaneously reduce PAR and total electricity bills. The planning model was based on an intelligent feeding system with distributed participants and a dynamic supplier that adjusts energy costs according to the required demand profiles. Although the DSM results show an 11.73% and 25.53% reduction in overall system PAR for DSM with and without battery, respectively, they overlook the inherent impact of variable daily load profile that may negatively influence and complicate the DSM process, so that each client can have an application scheme based on their needs, priorities and requirements. Similarly, a decentralized residential framework for 50 participants is presented in [19]. The home load management coordination problem is modeled as a bi-level optimization problem, where the upper subproblem looks for the modification of the system load profile and the lower level save individual demand tariffs. A rate of 20.5% decrement in the peak load is achieved by utilizing load management in non- cooperative load management (NCLM), while it is decreased to 16.8% when the cooperative load management (CLM) modules are realized. However, a variety of application use scenarios are not available to demonstrate the broad application of the proposed model. Most recently, an extension of multi-objective mixed integer linear programming (MMILP) model is proposed in [20] to solve the households' appliances scheduling problem taking into account consumer preferences and a peak load discount. The numerical experiments in this study show that the peak load is significantly reduced by 20% compared to unplanned energy consumption. Indeed, different individual electricity demand management approaches have been considered and tested. However, the re- planning of users' activities may be impracticable at the community level.

1.3 Contributions

Although the significant profits of price-based programs to individual consumers (i.e., the total cost), these results can be much worse than the optimum performance achieved through a coordinated load management strategy [21, 22]. It is necessary to have a scheduling algorithm that handles one more step, and to consider a new collective framework that can vastly outperform the optimal performance obtained by price-based consumers. The previous literatures [18, 19, 23] considered collective demand management that assumed that consumers opted for invariable monthly/weekly or daily demand power models and that predetermined preferences did not change. It implies that these strategies always keep the same daily use of demand, which means that these strategies do not change differently for multiple energy consumption profiles. However, in the proposed model, a variable energy consumption design is adopted, and participants may select a different daily demand profile. For example, a consumer may prioritize a home unit, but change it tomorrow, and even the home appliances may not remain the same.

The ultimate contributions of this paper can be summarized as follows:

- Proposing a cooperative game framework by modeling various number of consumers aiming to eliminate rebound peaks, decrease the PAR and improve cost savings at individual and large consumer levels.
- Investigating the impact of varying load demand usage by implementing efficient and flexible energy demand scheduling algorithm that address flexible consumption models using different scenarios.
- Developing a simulator interface to facilitate a direct interaction with the energy management system (EMS).
- Designing a generalized load management model by conducting various simulations to validate its usefulness and applicability, to preserving simultaneously users' preferences and maximizing energy demand saving at individual and commons plans.
- Proposing a pricing-based scheme for complexity analysis. By performing the comparison with the proposed approach for energy consumption scheduling, we confirm that the main findings of our proposed algorithm outperformed the pricing-based load management strategy. In addition, the proposed algorithm is more advanced than existing works.

1.4 Paper Organization

The remainder of this paper is organized as follows. Section 2 presents the collective energy scheduling model. Then, Sect. 3 describes the collective energy consumption scheduling framework with its general community goals. Section 4 summarizes the most important results and highlighting avenues for further research. Finally, the generic findings and acknowledge limitations are concluded in Sect. 5.

2 Model of the Aggregated System

In this study a load scheduling game model is proposed to address peak load savings, PAR reduction and energy expenses minimization. Four smart controllable appliances are included: an EWH, HVAC units, EV, and CD systems, in addition to a set of non-shifftable building units that will be taken as fixed vector components. Their operation time is unpredictable. Therefore, the CECS could not interrupt it. The main objective is to find the profitable decision of making ON/OFF hourly status of each shifftable appliance.

$$G = \{C;\{S_{i,t}\}_{i=1}^{C}\{\mathrm{P}_{i,t}\}_{i=1}^{C}\{\rho_{i,t}\}_{i=1}^{C}\} \tag{1}$$

$$\rho_{i,t} = \sum_{t=0}^{H} \sum_{i=1}^{C} R_t * P_{tot}(t) \tag{2}$$

$$M_{m,t}^{\alpha} \triangleq \left[M_{m,t}^{1}, M_{m,t}^{2}, \dots, M_{m,t}^{C} \right] \tag{3}$$

$$N_{n,t}^{\alpha} \triangleq \left[N_{n,t}^{1}, N_{n,t}^{2}, \dots, N_{n,t}^{C} \right] \tag{4}$$

$$P_r = \begin{pmatrix} P_{r1,1} & \cdots & P_{r1,C} \\ \vdots & \ddots & \vdots \\ P_{rm,1} & \cdots & P_{rm,C} \end{pmatrix} \tag{5}$$

$$P_{tot}^{\max} = \max_{t \in H} P_{tot}(t) \tag{6}$$

$$P_{tot}^{avg} = \frac{1}{H} \sum\nolimits_{t \in H} P_{tot}(t) \tag{7}$$

$$PAR = \frac{P_{tot}^{\max}}{P_{tot}^{avg}} = \frac{H \max_{t \in H} P_{tot}(t)}{\sum_{t \in H} P_{tot}(t)} \tag{8}$$

$$\theta_{t+1} = \theta_t + \Delta\theta \cdot \frac{G_i}{\Delta c} + \Delta\theta \cdot \frac{C_{HVAC}}{\Delta c} \cdot D_{HVAC,t} \tag{9}$$

$$\begin{aligned} \theta_{outlet,t+1} = & \frac{\theta_{outlet,t}(V_{\tan k} - fr_t \Delta t)}{V_{\tan k}} + \frac{\theta_{inlet} fr_t \Delta t}{V_{\tan k}} + \frac{1gal}{8,34lb} \\ & \left[P_{EWH} * \frac{3412Btu}{kWh} - \frac{A_{\tan k}(\theta_{outlet,t} - \theta_a)}{R_{\tan k}} \right] \\ & \frac{\Delta t}{60\frac{\min}{h}} \frac{1}{V_{\tan k}} \end{aligned} \tag{10}$$

$$\theta_{EWH} < \theta_{outlet,t} < \theta_{EWH} - \Delta\theta_{EWH} \tag{11}$$

$$t_{accum} < t_{required} \,\&\, t \geq t_{CD}^{start} \tag{12}$$

$$SoC_t = SoC_{t-1} + P_{EV} \frac{\Delta t}{C_{Bat}} \tag{13}$$

$$P_{ctr}(t) + P_{unc}(t) \leq P_{\lim it}(t) \tag{14}$$

$$P_{tot}(t) = P_{ctr}(t) + P_{unc}(t) \tag{15}$$

$$\begin{aligned} P_{ctr}(t) = & P_{EWH} \times D_{EWH,t} + P_{HVAC} \times D_{HVAC,t} + \\ & k \times P_{CD} \times D_{CD,t} + P_m + P_{EV} \times D_{EV,t} \end{aligned} \tag{16}$$

$$D_{\alpha,t} = \begin{cases} 1, & appliance\ \alpha\ is\ active \\ 0, & appliance\ \alpha\ is\ inactive \end{cases} \tag{17}$$

As mentioned earlier, the implemented CECS algorithm can be considered as a game theory problem (Eq. 1), in which C are set of households or the players aiming to minimize their energy cost $\rho_{i,t}$ and increase the energy savings $P_{i,t}$ under a common community objective. To implement the proposed CECS strategy three inputs namely the shifftable load vector $M_{m,t}^{\alpha}$(Eq. 3), the non-shifftable load demand $N_{n,t}^{\alpha}$(Eq. 4), and the predetermined time preferences of each smart appliance (Eq. 5) will be created based on user daily needs and behaviors. Since the central level is responsible of data gathering; the hourly information is sent to smart meters and the components of these inputs can also change during different days, so these are a time varying vectors. The PAR in load demand is calculated based on Eq. 8. In general a lower PAR value referred to minimum outages of the main system and most low operating expenses [24]. Where $P_{tot}^{\max}$ and P_{tot}^{avg} are the individual daily peak load and the average load, respectively. Equation 9 specifies the one thermal parameter for HVAC system modeling. Where at each time slot t, the HVAC should operate whenever the room temperature is greater than the maximum temperature range. Therefore the user will set the upper and the lower comfort temperature range $\theta_{\max}$ and $\theta_{\min}$, respectively. If the room temperature exceeds the comfort temperature limit the HVAC is tuned on otherwise it is inactive [25, 26]. Equation 10 represents the temperature inside the tank, used to control the running cycle of the EWH. The formula in Eq. 11 sets the room temperature limits to keep users comfort. The clothes drying operation is divided into two parts. The high power consuming one (several kilowatts) is the heating coils part, and the motor one that can not be controlled by the CECS without user intervention. This second part consumes less power (some watts). Therefore, the energy consumption management system decides to start or stop working just the heating coils. The CD runs according to the accumulated time of drying operation Eq. 12. Each user will set the upper and lower. Commonly bi-directional EV charging is considered; the grid to EV or EV to grid minimizes the demand on high energy prices [27, 28]. Furthermore, in this chapter the EVS are treated as any controllable electrical device, an unidirectional way of electricity is considered to charge its battery, what increase the complexity of the proposed model since if multiple EVs are simultaneously need to be charged a significant demand peak can be introduced. The charging schedule of EV is similar to that presented for the CD operation, since the user should set the desired start charging time and the required fully charge state of the battery. At each time t, the state of charge of the battery is formulated as Eq. 13. The energy consumed by the controllable devices for each participant having those units must be lower than power limit. The constraint shown in Eq. 14 indicates that at each time step t, the sum of power consumed by each household must be lower than maximum power usage defined by the energy manager system. The terms $D_{\alpha,t}$ in Eq. 16 represent the operational state of the respective appliances. The uncontrollable power (P_{unc}) refers to all other consumed power in the household other than the four shifftable devices considered in this paper. Equation 17 specifies the activation function for controllable appliances after CECS decisions. If the appliance is active, its nominal power is absorbed, no usage power otherwise. In the CECS model, it assumed that home users do no communicate with each other due to privacy conditions. The coordination strategy is deployed in two consecutive levels: firstly the data collection among smart meters, and secondly a game theory with a Nash Equilibrium is presented to coordinate schedules repeatedly. From Eq. 1, the deployed game theory is defined as follows:

Players: each user $i \in C$ in the neighborhood area.

Strategies: Selected load management schedules $\{\mathrm{P}_{i,t}, \rho_{i,t}\}$ for each user $i \in C$ to maximize its payoffs.

$$\mathrm{P}_{i,t} = [\mathrm{P}_{i,1}, \mathrm{P}_{i,2}, \ldots, \mathrm{P}_{i,H}] \tag{18}$$

$$\rho_{i,t} = [\rho_{i,1}, \rho_{i,2}, \ldots, \rho_{i,H}] \tag{19}$$

where $\mathrm{P}_{i,t}$ and $\rho_{i,t}$ are the strategies for all participants except i for consumed power and electricity price profiles.

$$U_i(\{\mathrm{P}_{i,t}, \rho_{i,t}\};\{\mathrm{P}_{-i,t}, \rho_{-i,t}\}) = -\rho_{i,t} \tag{20}$$

Definition1 The Nash equilibrium is a solution concept in which each user selects its desired power usage to improve its payoffs.

$$U_i(\{\mathrm{P}^*_{i,t}, \rho^*_{i,t}\};\{\mathrm{P}^*_{-i,t}, \rho^*_{-i,t}\}) \geq U_i(\{\mathrm{P}_{i,t}, \rho_{i,t}\};\{\mathrm{P}^*_{-i,t}, \rho^*_{-i,t}\}) \tag{21}$$

where $*$ indicates the strategy of each variables type at Nash equilibrium state.

Theorem 1 *The defined energy consumption game* $G = \{C;\{\mathrm{P}_{i,t}, \rho_{i,t}\}_{i=1}^{C}; U_i\}$ *exists.*

Proof 1: $\rho_{i,t}$ convex for each time slot t and the payoff $(U_i(\{\mathrm{P}_{i,t}, \rho_{i,t}\};\{\mathrm{P}_{-i,t}, \rho_{-i,t}\})$ is a concave function with respect to $\{\mathrm{P}_{i,t}, \rho_{i,t}\}$. Consequently, referring to [29] the Nash Equilibrium exists.

3 Proposed Model

The general design of CECS is given in Fig. 1. In this schematic, various residential buildings (RBs) exist with controllable uncontrollable appliances and Home Load Management Modules (HLMMs) implanted in households smart meters. Each HLMM is used to schedule the demand load for RB and exchange management information among the neighborhood area. As shown in Fig. 1, the implemented CECS framework plans the energy consumption under two levels: (i) the local scheduling phase (LS), and (ii) central scheduling (CS) phase. The LS is the internal demand scheduling system that is focused on the collection of individual data (consumers' requirement, tasks activation time, load duration, load priorities, etc.). Then, it sends these data information to the CS or the external level of energy management. This later is responsible to collaborate individual desired plans and found their interaction with the global goal of reducing peak load consumption in the whole community. Moreover, the flowchart related to the pseudo code.1 is given in Fig. 2. After individual data gathering, the local level announces individual plans for load profile to each HLMM. The CECS system at the central level investigate the individual load profiles and elaborate the proposals load profiles comprising the main goal of a total peak load saving, PAR minimization resulting a significant economic profit. The proposed approach considers a collective plan to achieve these perspectives. The CS system send CECS proposals and recommendations to individual HLMMs to modify their load profiles.

Schedules with accepted decisions are updated. This operation is repeated until no further modification in the system load profile is announced. It should be noted that the local improvements of energy profiles are iteratively evaluated to judge its economic and technical benefits i.e., the CS for the energy demand system investigates gathered demand change proposals individually, until

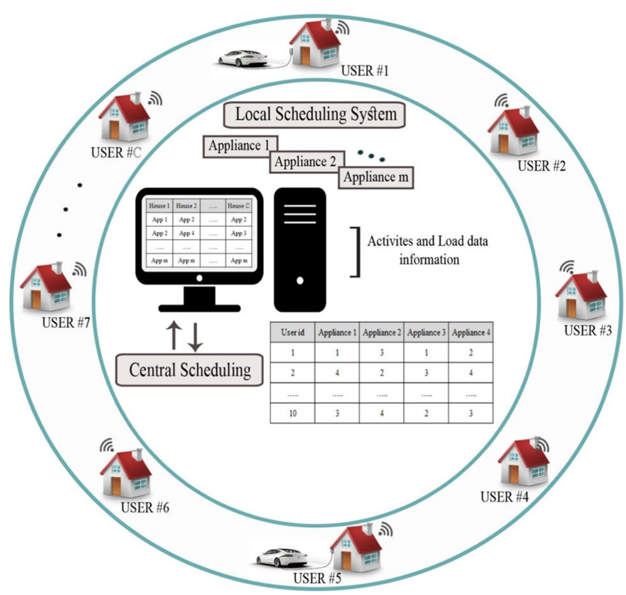


Fig. 1 Neighborhood grids under study

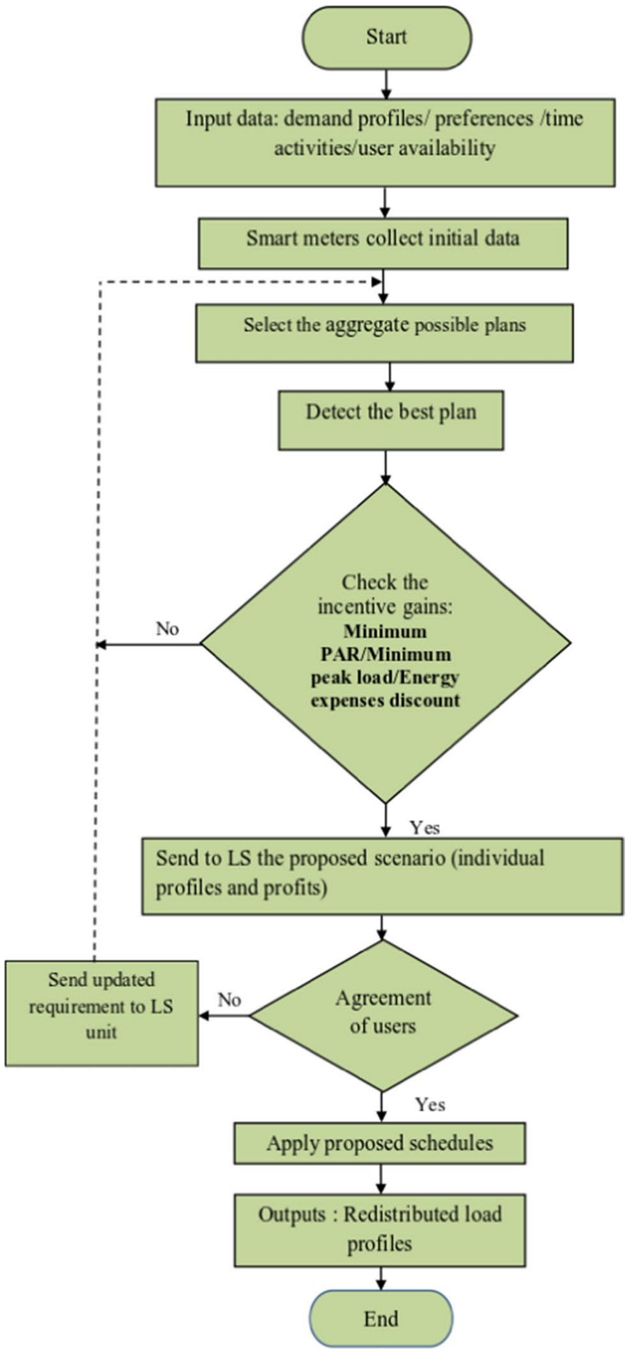


Fig. 2 Flowchart of implemented CECS

guarantee the achievement of all requirement of different players. The coordinated demand planning is based on shifting and cycling time activation of controllable appliances while collating combination of plans, considering neighbor's interaction. Therefore, required improvements are obtained according to limitations including appliances' operational characteristics, instructions and limits, besides preserving the customers' preference. The implemented CECS algorithm is executed in a daily cycle and composed of three parts summarized as follow:

Algorithm 1: Pseudo-code related to the proposed CECS

Input: Desired objectives $G = \{C; \{S_{i,t}\}_{i=1}^{C}; \{P_{i,t}\}_{i=1}^{C}, \{\rho_{i,t}\}_{i=1}^{C}\}$

Set the aggregated area profiles, area energy cost
While (users change their decisions)
Repeat
for *t = 0*
for *C =1*
Energy scheduling game (found intersection of different demand plans)
$peak = max\left(peak_1, .., peak_H\right)$
$PAR = \frac{P_{tot}^{\max}}{P_{tot}^{avg}} = \frac{H \max_{t \in H} P_{tot}(t)}{\sum_{t \in H} P_{tot}(t)}$
Until convergence is achieved (Nash Equilibrium energy scheduling game)
The energy management system send recommendations to all users.
if all participants follow proposed actions
then updates load plans
else
send modifications to the LS
end if
$t = t + 1$
$C = C + 1$
end repeat

Output: Optimal load profile

Data gathering: In this step, the data required for the simulation is feed into the energy management system. It involves the predetermined priorities of each user, the forecasted demand curves according to user activities and plans, parameters of the appliances and also the participant availability for the following day.

Scheduling problem resolution: As introduced previously the CECS workflow is formed in a coordinated level in which the energy demand management system should find the junction of each candidate action under a community benefit. For this, each user equipment's preferences are defined in this step as a vector of H hours in addition to the desired time activities of each appliances. Once the data is collected the CECS is able to be run. After the combination of scheduling plans by solving Eq. 1 to select (in Nash Equilibrium) the best consumption profiles. The set of recommendations are stored in a matrix of $'C \times H'$ composed by the energy consumption of the whole group. From this step, it is possible to present the accounting of energy demand of each individual consumer in addition to the aggregated demand curve of the residential community.

Validation of users for the proposal plans: It is a fundamental part of the proposed EM system. The users are informed by the proposed schedules, containing the PAR reduction, the peak load minimization rate, energy demand cost gain. Consumers are permitted to change the beginning or ending time activation of an appliance or they may change their priorities. These modifications are sent to scheduling resolution phase again. By executing the CECS algorithm, an updated consumption matrix is reselected. Since the proposed approach ensures both cooperative and individual benefits, this step is repeated until the adoption of all users' agreements.

4 Numerical Simulations

4.1 The Proposed CECS user Interface

The graphical user interface was developed in the C# simulation tool as a strong, simple and well-performed type of object-oriented language [30]. As presented in Fig. 3, this simulator considers the parameters of each user including (temperature, load profile, appliances preferences, availability of users…). These parameters can be changed under the CECS recommendations. Finally, the proposed CECS schedules executed under the primary parameters fed into the interface are presented to users. It offers easy access to participants to the day-ahead scheduling by a personal computer providing detailed information about the total consumption saving and the optimal activation time of each controllable appliance. In the following sub-sections, the obtained results by the implemented CECS are presented and analyzed.

4.2 Data Preparation and Studied Scenarios

The following appliances HVAC, CD, EWH and EV present the most energy consumption in U.S according to [31]. The developed model considered a minute-interval for weather data for a typical day in May. The appliances' parameters are referred to the data presented in [22, 32–36] and main parameters are summarized in Table 1. The multiple studied homes are categorized based on ownership of appliances and predetermined load's preferences which are listed in Tables 2, and 3, respectively. In this section, the proposed approach is evaluated supposing different scenarios in order to demonstrate its improved performance. The first scenario, presents a classic test, we assume that buildings hold similar appliances with a stationary energy consumption profiles.

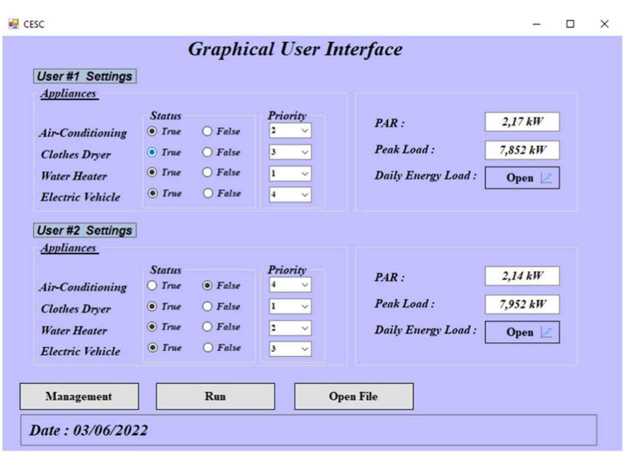


Fig. 3 Proposed CECS graphical user interface

Table 1 Appliances parameters

Parameters	Value
Water heater	
$V_{\tan k}$(gallon)	Uniform volume between 20 and 80
$A_{\tan k}\left(\mathrm{ft}^2\right)$	14
$R_{\tan k}\left(°\mathrm{F\,ft}^2\,\mathrm{h/Btu}\right)$	Uniform resistance between 12 and 25
P_{WH}(KW)	4.5
Δt(min)	1
θ_W(°F)	Uniform temperature between 110 and 120
$\Delta\theta_{WH}$(°F)	Uniform temperature between 5 and 10
Air conditioning	
θ_s(°F)	Uniform temperature between74 and 78 for summer days, and between 66 and 72 for winter days
C_{HVAC}(Btu/h)	33
$\Delta\theta_{AC}$(°F)	2
P_{AC}(kW)	2352
Clothes dryer	
P_m(kW)	0.3
P_{CD}(kW)	3.7
Electric vehicle	
P_{EV}(kW)	3.3
$C_{Battery}$(kWh)	24
$SoC_{\max}$(%)	100

Table 2 Homes analyzed by their sets of appliances

House-identification	EWH	HVAC	CD	EV
1	×	✓	✓	✓
2	✓	×	✓	✓
3	✓	✓	×	×
4	✓	✓	×	✓
5	✓	✓	✓	×
6	✓	×	✓	✓
7	×	✓	✓	×
8	✓	×	✓	✓
9	×	✓	✓	✓
10	✓	✓	✓	✓

Table 3 Homes analyzed by their load's preferences

House-identification	EWH	HVAC	CD	EV
1	1	2	3	4
2	4	1	3	2
3	1	2	4	3
4	2	3	1	4
5	3	4	2	1
6	2	1	3	4
7	1	4	2	3
8	4	1	3	2
9	2	4	1	3
10	3	1	2	4

Customers are permitted to change their pre-defined load's priorities for the following day scheduling.

The proposed schedules are updated until satisfying all user's requirements, then the CECS method generates the day-ahead re-planning of load devices with a resolution of 1 min. In the second scenario, the impact of different load profiles is investigated by changing the number of devices in each home. While in the third scenario, the load schedules are decided by assigning different appliances' priorities values what increase the system complexity. The last case is referred to energy consumption scheduling with variation of predetermined loads preferences and owned shifftable appliances.

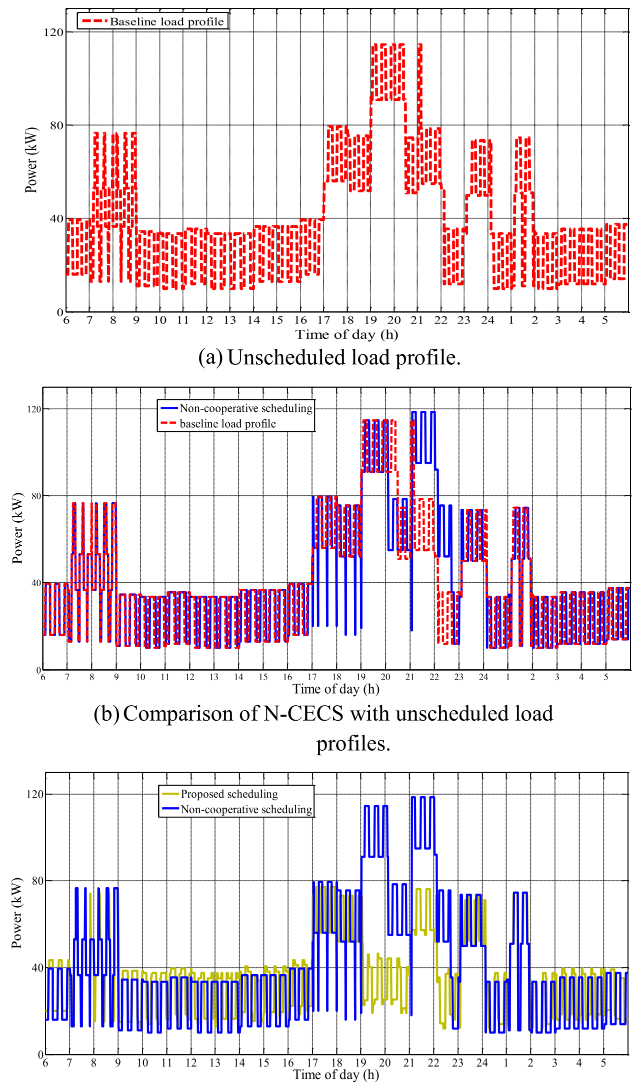
For each above-mentioned scenarios, three load scheduling models are simulated: (1) before load management, (2) non-cooperative or price-based load management (N-CECS), and (3) the proposed cooperative energy consumption scheduling (CECS).

Model 1: Without load management

This case is considered as a reference case. In this model, the simulations are carried out with no pricing-based or coordination schemes. The algorithm did not consider an intelligent redistribution of time-shifftable appliances, i.e. EV and CD, only the control the HAVC and EWH is adopted. Indeed, the controllable appliances are working immediately when consumers turn them on Figs. 4a, 5a, 6a and 7a, show the simulation results for the baseline load profiles under different users' parameters as mentioned earlier.

Model 2: Non-Cooperative/price-based demand energy management. (N-CECS)

This case is considered as a traditional scheduling scenario. It occurs when users monitor their load profile selfishly without considering a collective goal. Indeed, there is no coordination between consumers, each one schedules its electricity demand individually considering the day-ahead TOU [37] and its load preference. In other words, controllable appliances are shifted to the lowest energy



(a) Unscheduled load profile.

(b) Comparison of N-CECS with unscheduled load profiles.

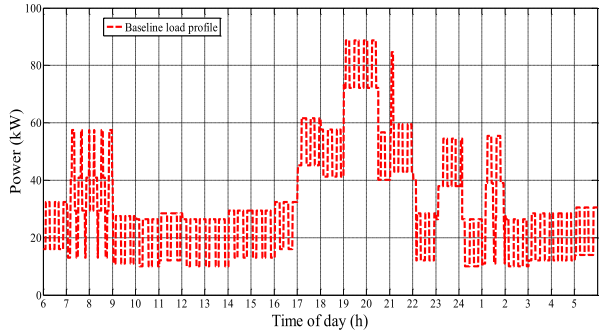
(C) Comparison of the N-CECS with the proposed approach.

Fig. 4 Power consumption under scenario 1

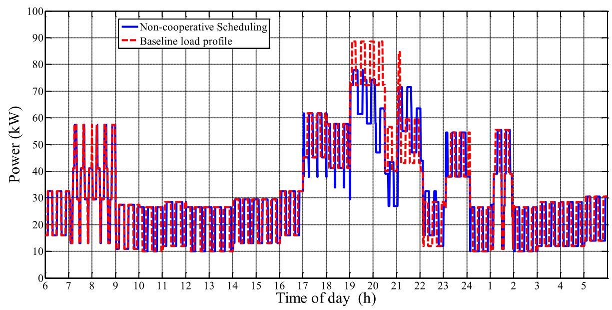
price periods (from 6 am to 2 pm or after 7 pm). In this scenario, it is assumed that time-varying prices are already being sent to customers for consideration in their response to load management. Therefore, the required re-planning is exchanged with the electricity service provider to evaluate individual monetary incentives. As mentioned previously, ToU tariffs are announced for the following 24 h in which the determined electricity price is dependent on the time delivery production block (on-peak, off-peak or super-off-peak duration).

Model 3: Cooperative energy consumption scheduling CECS

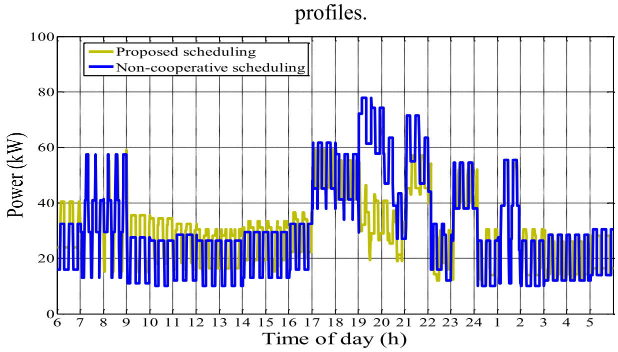
This case is referred to the same smart grids with the proposed CECS program. The framework schedules consider the neighbor's preferences, and it applied when



(a)Unscheduled load profile.

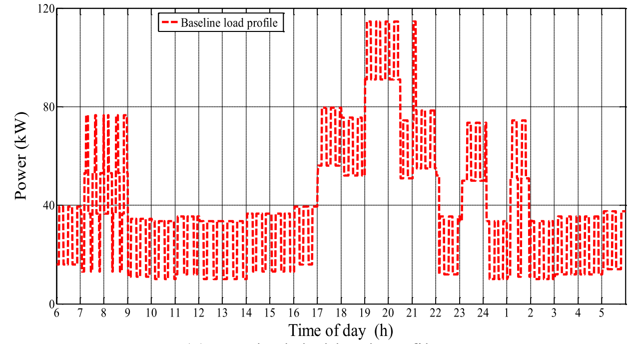


(b)Comparison of N-CECS with unscheduled load profiles.

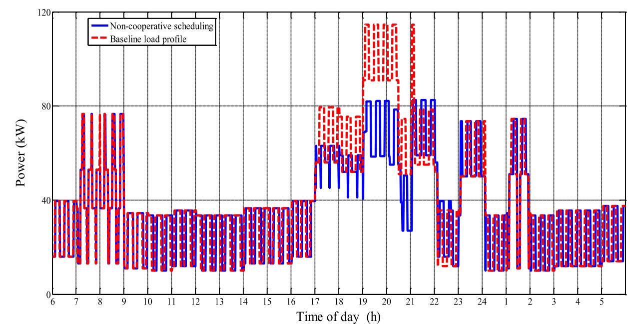


(C)Comparison of the N-CECS with the proposed approach.

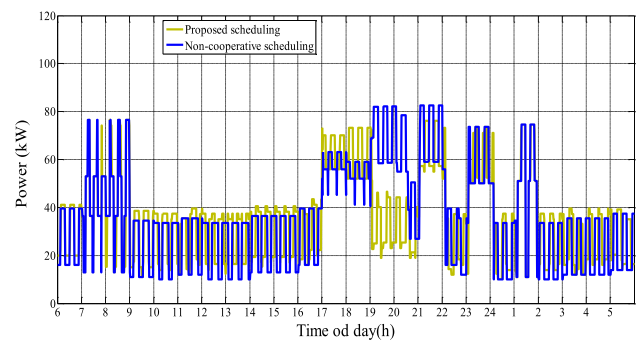
Fig. 5 Power consumption under scenario 2



(a)Unscheduled load profile.



(b)Comparison of N-CECS with unscheduled load profiles.



(c) Comparison of the N-CECS with the proposed approach.

Fig. 6 Power consumption under scenario 3

consumers are willing to collaborate their data in order to solve the rebound peak problem and to reduce total energy cost. Algorithm 1 presents the main steps of the scheduling method. As described the proposed CECS considers a central- level and local- level for load management problem.

4.3 Performance Evaluation

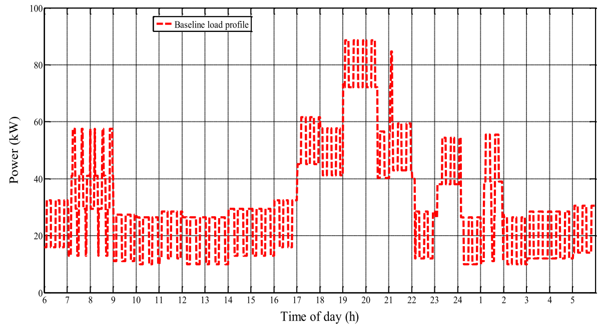
Neighborhood-level metrics are procured from the simulation findings:

PAR of overall daily consumption: parameter that evaluates the effectiveness of the energy consumption scheduling. It is expressed as the ratio between the maximum demand power and the average consumed power.

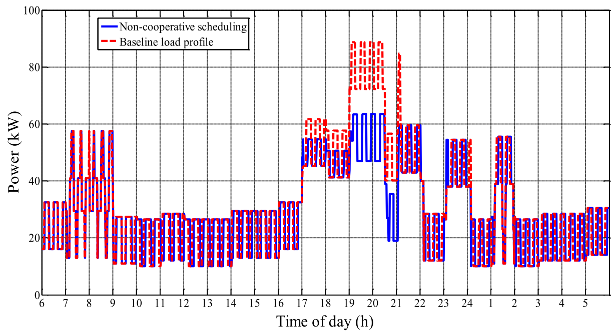
Overall community cost: the total electricity bills at community level using the day-ahead planning model.

Peak load demand: the maximum demand power of total profile after applying the scheduling model.

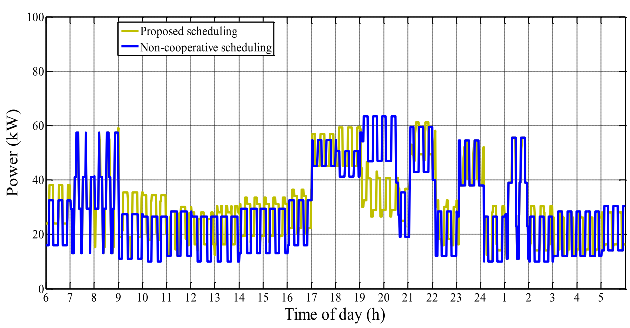
First, the analysis of the N-CECS based on TOU pricing with the baseline load profiles is investigated for the four scenarios. Figures 4b, 5b, 6b, and 7b, compare the aggregated load profiles of the whole community after and before implementing the N-CECS program. It is clear that, with the involvement of load scheduling based on time varying prices, most controllable loads are shifted to the same hours (low-pricing periods), which resulting major power imbalances in the daily planned loads. Specifically, peak rebounds are produced during the off-peak periods (between 7 and 11 pm), when prices are the lowest and multiple households



(a)Unscheduled load profile.



(b)Comparison of N-CECS with unscheduled load profiles..



(c) Comparison of the N-CECS with the proposed approach.

Fig. 7 Power consumption under scenario 4

consume at the same time. Moreover, as shown in Fig. 4b the peak load is higher after the N-CECS, especially when all consumers required the same preferences and devices (118.52 kW). This is can be explained by the uncoordinated behaviour of the second model (N-CECS), each customer schedules their appliances activation during the low-pricing periods for electricity payment savings. Therefore, overloads at these periods might be occurred. Although Figs. 5b, 6b and 7b show that around 12.18%, 27.94%, 28% saving in the maximum load demand are taken into account in the N-CECS implementation, the total findings based on N-CECS prove significant violations at the grid operational restrictions (rebound spikes). So, it can be concluded that the load scheduling based on time varying electricity prices should not be applicable for all systems and requirements. In this case, the performances of the stationary price-based method achieved by appropriate tariff schemes are suboptimal.

At a second step, the results of implementing the proposed collective load management model are shown and compared to the N-CECS. Figures 4c, 5c, 6c and 7c compare the consumption curves after implementing the CECS system and with N-CECS scheduling. It is doubtless that after implementing the proposed CECS scheme, the peak load are largely minimized, and rebound peaks are avoided. Indeed, the proposed method can make good balance between multiple user preferences, power consumption, and controllable appliances by selecting the proper starting time to switch on,while reduce the power consumption by up to 33%. As depicted in Figs. 4c, 5c, 6c and 7c), the total daily energy consumption for all the four tested scenarios are proving that the driven N-CECS peaks are higher than for the peak loads resulted from the CECS scheme. Moreover, Figs. 4c, 5c, 6c and 7c) show an obvious decrease in maximum load of 32.61%, 33.10%, 33.2% and 28.42%, respectively for Scenario 1, Scenario 2, Scenario 3 and Scenario 4. In addition, as can be observed in Fig. 4c, the load profile in CECS scheme is significantly different from the one in N-CECS strategy due to the elimination of demand rebound spikes at low-pricing time intervals through effective CECS participation. The summary table (Table 4) shows that with the comparison of four studied scenarios. It can be found that with coordination the proposed approach can both save energy

Table 4 Summary of the achieved metrics under differ-ent studied models

Metrics	Scenarios							
	(1)same P_r, same home appliances		(2)same P_r, different home appliances		(3)different P_r, same home appliances		(3)different P_r, different home appliances	
	Non-cooperative scheduling	Cooperative scheduling	Non-cooperative scheduling	Cooperative scheduling	Non-cooperative scheduling	Cooperative scheduling	Non-cooperative scheduling	Cooperative scheduling
Peak load profile (%)	– 3.49	32.61	12.18	33.10	27.94	33.2	28	28.42
Community cost ($)	74.33	62.96	54.90	52.64	64.52	62.19	53.69	52.00
PAR	2.83	2.128	2.49	1.95	2.22	2.12	2.126	1.98

cost and reduce peak loads for each scenario in comparison to the metrics associated with N-CECS. Scenarios 2 and 3 presented the most decreased peak load demand under the CECS approach. Furthermore, scenarios 2 and 4 presented the lowest expensive under the recommended CECS profiles. Similarly, scenarios 2 and 4 resulted in the lowest PAR in comparison to other scenarios under the proposed approach.

Figure 8 helps to more appreciating the result community demand profiles for both N-CECS model and CECS model. Scheduling with CECS can maintain the peak load demand to 78 kW, whereas scheduling with N-CECS scheme have a peak load demand distribution in the high range (reaching until 118 kW in the first scenario). It implies that consumers should get some shaving in their energy consumption for the low price period, and vice versa. According to Fig. 8a, we note that the tallest moustache is at its maximum, which signifies a longer tail to the highest values. This suggests that about 50% of the load profiles match the most extreme peak load demand values. Unlike Fig. 8b, the CECS algorithm is able to produce the most consistent minimum compared to

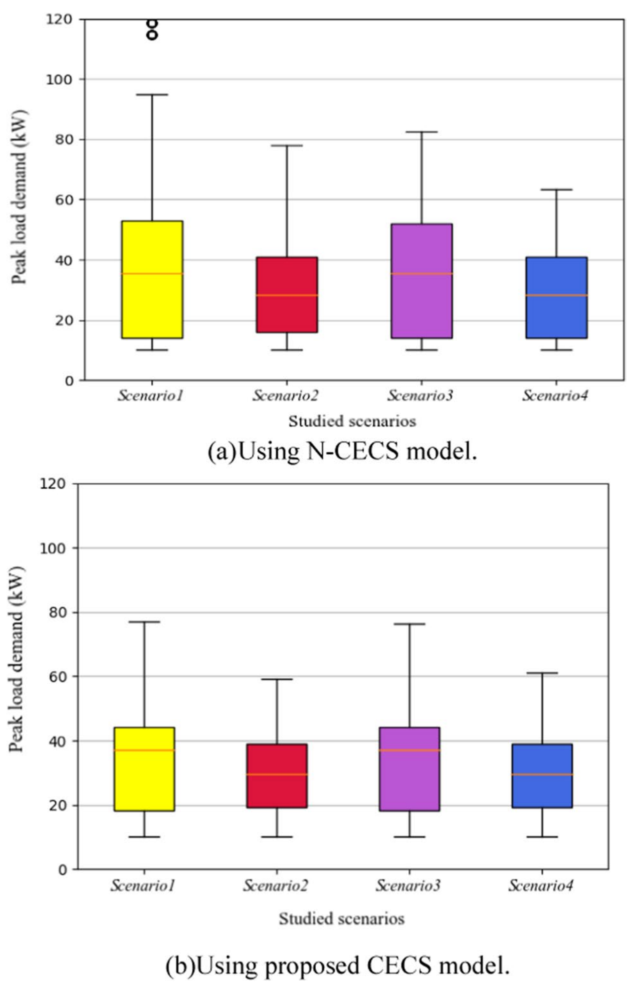


Fig. 8 Maximum load demand in the whole community

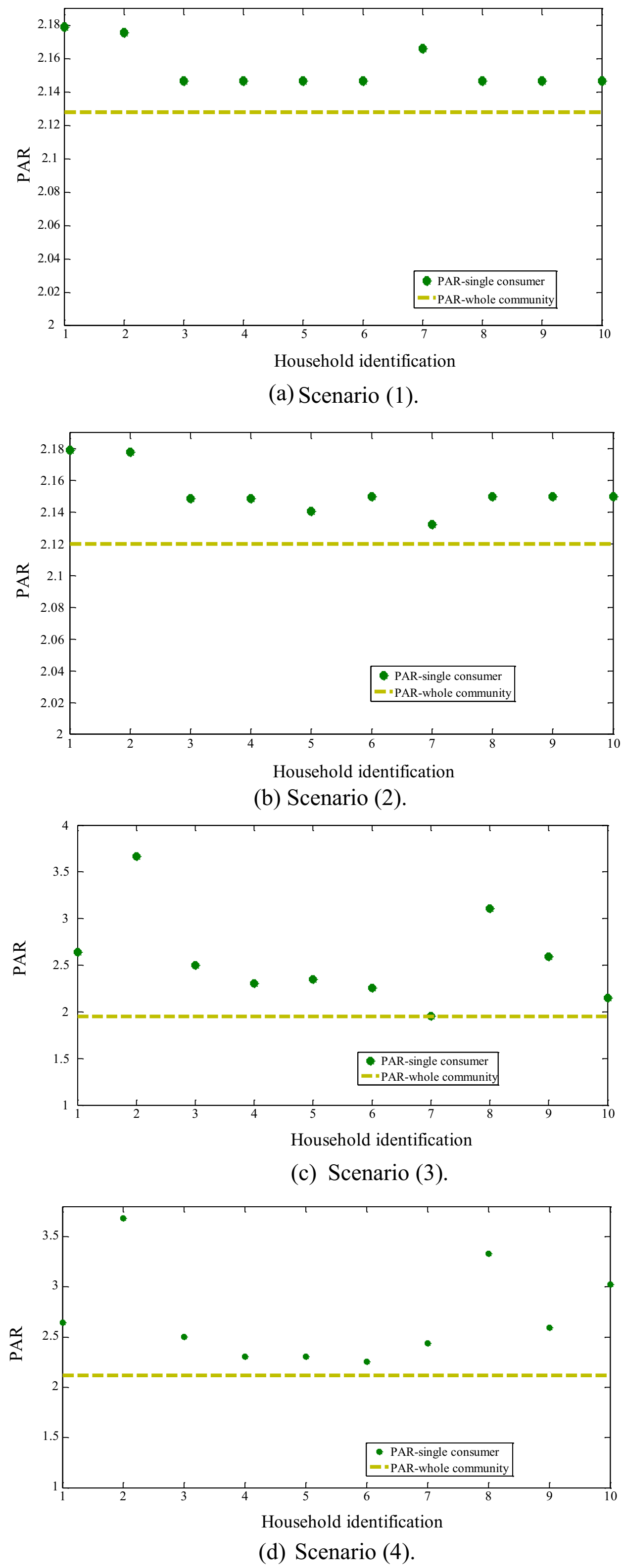


Fig. 9 PAR in individual daily load and comparison with PAR driven schedules under different scenarios

Table 5 Comparison of profits achieved by different algorithms

References	Analyzed load profiles		PAR reduction (%)	Cost minimization (%)	Peak load minimization (%)
[17]	Non- varying		Not considered	15.6	15.6
[18]	Non- varying		> 1.73	Not considered	Not considered
[19]	Non- varying		Not considered	1.8	16.8
[20]	Non- varying		Not considered	Not considered	> 10
Proposed model	Non- varying	Scenario1	25.29	11.8	32.61
Proposed model	Non- varying	Scenario2	28.8	7.46	33.1
Proposed model	Non- varying	Scenario3	25.41	12.50	33.2
Proposed model	Non- varying	Scenario4	27.8	8.56	28.42

the uncoordinated load scheduling model, i.e. N-CECS. On the other hand, to prove the efficiency of the proposed load scheduling strategy on the reliability of both the single and aggregated findings, different PAR spectra of ten homes are illustrated in Fig. 9a–d. It is obvious from Fig. 8, that the cooperative PAR is significantly less than the PAR in each consumer's individual load. Thus, appropriate schedules are obtained for individual users, while conserving the global community profit. Indeed, the implementation of CECS schedules is very effective in reducing PAR compared to two other models, resulting in significant community and individual benefits at the same time.

To sum up, these simulation results demonstrated that: (1) the proposed CECS successfully eliminates rebound peaks by avoiding load accumulation at low price hours. (2) The cost of electricity consumption is lower in the proposed CECS strategy than in the N-CECS scheme for all tested load profiles. (3) The PAR in the proposed CECS model is greatly reduced simultaneously for individual and community scales, which measures the efficacy of the proposed CECS algorithm.

4.4 Comparison with Existing Collective Scheduling Mechanism

In this subsection, the proposed CECS is compared with the existing DSM approaches. The comparison targets the same contributed objectives: PAR [17, 18], peak load minimization [17, 19, 20], and consumption cost reduction [17, 19, 20]. Based on the same collective goal of energy management across different smart grids. The comparison is restricted to total profits. Based on these five algorithms, the summary is presented in Table 5. It can be seen the PAR associated with the CECS based schedules is 53.6% less than the PAR associated with demand side management schedules in ref. [18]. When it comes to reducing energy costs, the CECS scheduling algorithm significantly exceeds the other two algorithms. The cost discounts compared to [19] are less by 84.7% and 93.5% respectively. Based on peaks in demand reduction under the CECS algorithm comparing to [17–20], a significant performance gain is achieved between 8 and 69.9%.

5 Conclusion

In this paper, an effective coordinated load management model for a large neighborhood smart grids is proposed. HLMMs controls the energy demand usages under heterogeneous customers' preferences and home appliances based on game theory approach has been established to obtain significant profits in terms of peak load reduction, PAR minimization and total bills minimization. Moreover, a graphical user interface has been implemented in the C# software environment to incentivize users for the evaluation of proposed CECS. The simulation results are conducted for various scenarios to prove the applicability of the proposed CECS model. The findings reveal that the proposed CECS-based scheduling strategy can largely avoid the negative impacts of the rebound peak power system and reduction in total peak load to approximately 33% of total peak load after CECS implementation. Furthermore, the proposed model improves cost savings till 18.05% and minimizes PAR by more than 43.7%. In addition, the model presented shows better performance in managing the complexity of the multiple preferences of users and devices in their possession and in realizing significant benefits at the individual and cooperative level.

Future extensions of this work could take into account the impact of a large number of appliances and power production constraints. In addition to the investigation of the local and total communication effect among users on the effectiveness of the proposed algorithm.

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