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Original article

Fairness-driven integrated multi-prosumer load scheduling incorporating solar energy

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A R T I C L E I N F O

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A B S T R A C T

Aggregation of flexible loads and power generation of solar photo-voltaic (PV) systems is considered as a valuable power resource in residential demand response (DR). Despite the rapid growth of smart appliances, there are few practical solutions for exploiting their potentials in DR load aggregation. In this paper, we present a practical multi-prosumer framework to enable the aggregator reach a minimum bidding power and participate in the wholesale market. This is attainable through directly rescheduling a large number of smart appliances and utilizing the surplus power generation of residential PVs. An optimization model is designed which maximizes the aggregator's profit while respecting customers convenience. Fairness is a significant component of this model ensuring fair selection of appliances for shifting by the aggregator and not biased toward customers availability. We investigate the model as a hard instance of the 0–1 Knapsack problem and devise a heuristic algorithm to cope with its time complexity and to improve its scalability. The simulation results of two large-scale case studies are presented and discussed. It is demonstrated that the proposed framework is beneficial to both the aggregator and its customers, leading to a greener environment.

Introduction

Dramatic advancement of human civilization in recent years is undoubtedly owed to electricity which also caused the continuous increase of power usage and the consequential environmental side-effects. It was projected that U.S. energy-related Carbon Dioxide (CO_2) emissions increase by 2.7% in 2018 [1]. Since extra power generation to match peak demand causes more CO_2 emission and imposes additional costs to the main grid, it is more desirable to utilize the capacity of loads flexibility or to send excess solar energies back to the grid.

Demand response (DR) programs are means to involve consumers to make change in their electricity demands by shifting or reducing them in response to either changes in the price over time or to the grid operator's requests for receiving financial incentives; these conditions happen when market prices are high, or reliability of the grid is jeopardized [2]. Conventionally, price-based DR programs with the aim of flattening the overall load curve, provided dynamic market price rates to customers to encourage them to modify their usage [3,4]. But, it is shown that these programs barely affected residential consumers' usage pattern [5,6]. Later, incentive-based DR programs were developed as an alternative load shaping solution, in which, participants receive incentives for load reduction when requested [7,8].

Current power markets prevent small residential consumers from participating in markets due to lack of enough controllable loads of those customers and the complexities in markets [9]. DR Aggregators are also known as for-profit intermediaries between wholesale market and consumers which aggregate consumers' demand reduction potentials to exploit wholesale market opportunities and in return, provide incentives or lower energy prices to the consumers. Prosumers are energy consumers who also installed rooftop solar panels to produce and to consume electricity at the same time [10]. Authors in [11] investigated the strategies to overcome "too small to bid" problem for flexibility aggregators.

Household appliances scheduling based on aggregator-offered prices and contracts have been extensively studied in previous works [12–14]. Authors in [15] proposed a model for optimally scheduling end-users appliances at their premises after receiving the aggregator's price offer

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Nomenclature

Indices

i	Index of smart appliance
h	Index of residence
j	Index of PV panel
t	Index of timeslot

Sets

T	Set of timeslots in the studied time-horizon
H	Set of residences
I	Set of smart shiftable appliances in all residences
J	Set of PV panels in residence h

Variables

$d_{i,h}^t$	Power demand of smart shiftable appliance i in residence h during timeslot t [kW]
c_h^t	Power demand of all non-shiftable appliances in residence h during timeslot t [kW]
G_h^t	Generated power by all PV panels in residence h during timeslot t [kW]
$P_{pv_{j,h}}^t$	Generated power by PV panel j in residence h during timeslot t [kW]
$Pr_{pv_{j,h}}$	Rated power of PV panel j in residence h [kW]
R^t	Solar irradiance in timeslot t [W/m^2]
$\eta_{i,h}$	Financial reward for shifting appliance i in residence h [¢]
η_h	Total financial reward for residence h [¢]
N_h	Total number of shifted appliances in residence h
$x_{i,h}$	Binary variable equals 1 if smart appliance i in residence h is shifted by aggregator and 0 otherwise
y_h	Binary variable equals 1 if power of PV panels in residence h is utilized by aggregator and 0 otherwise
$a_{i,h}^t$	Binary variable equals 1 if operating of appliance i in residence h is authorized in timeslot t and 0 otherwise
$L_{rd_{pv}}^t$	Total reduced load in timeslot t from all PVs' excess generated power [kW]
$L_{rd_{pv}}$	Total reduced load from all PVs' excess generated power during peak-time interval [kW]
$LR_{i,h}$	Reduced load from shifting smart appliance i in residence h [kW]
$LS_{i,h}$	Restored load after shifting smart appliance i in residence h [kW]
$CR_{i,h}$	Cost of load reduction for shifting smart appliance i in residence h [¢]
$CS_{i,h}$	Cost of load restoration for shifting smart appliance i in residence h [¢]
RN_h	Aggregator's revenue from utilizing PVs' excess generated power in residence h [¢]
$L_{rd_{sh}}$	Total reduced load from shifting selected appliances [kW]
L_{rs}	Total restored load after shifting selected appliances [kW]
X^t	predicted market price for timeslot t [¢/kWh]

Constants

$EST_{i,h}$	Earliest Start Time for the operating of smart appliance i in residence h (defined by consumer) [h]
$LFT_{i,h}$	Latest Finish Time for the operating of smart appliance i in residence h (defined by consumer) [h]
$PST_{i,h}$	Pre-scheduled (preferred) start time of smart appliance i in residence h (defined by consumer) [h]
λ^t	Market price for power consumption in timeslot t [¢/kWh]
$K_{i,h}$	Number of timeslots for appliance i in residence h
Θ	Required amount of load reduction [kW]
t_{bp}/t_{ep}	Timeslot associated with the beginning/end of peak-time interval [h]
SH_{Rew}	Base reward for shifting smart appliances [¢]
PV_{Rew}	Reward for utilizing household PVs generated power [¢]
W	Weight of reward increment rate
S	Number of price scenarios

for energy usage modification in a specific time interval. In [16] consumers who participate in the aggregator's DR programs sign contracts and upon receiving load reduction request signals via their smart meters, modify their usage for receiving rewards. Consequently, the aggregator can enter the wholesale market and trade the aggregated power from overall load reductions in peak hours. In [17], household customers willingly submit their bids to shed their appliances' loads for the price they want to pay, then the service provider aggregates customer's bids and provides an overall load profile. Authors in [18] studied the rescheduling of electricity consumption for large customers. However, in aforementioned studies, the scheduling problem is investigated in each single premises, then the aggregator collects the aggregated power saved by all customers in certain time intervals for further actions. On the other hand, in these studies, the aggregator needs to establish its strategies for participating in market based on consumers' responses while the estimation of consumers' responses to the signals is complex in nature and put the aggregator at risk [19]. In addition, when price-based demand response programs implemented in large-scale, stability of the grid may be violated [20].

Regarding integrated demand response, a recent study [21] developed a Stackelberg game between energy operator and users for integrated demand response scheduling and coordination of renewable energy resources. Authors in [22] designed an integrated demand response model for smart energy hubs followed by a game to maximize operators' profit and to minimize costs for customers simultaneously. However, the aforementioned studies are either designed to be embedded as a part of a home energy management system or customers are followers responding to operator's prices/signals and the problem of integrated smart appliances scheduling and aggregating PVs generations by aggregator in large-scale is not investigated.

There is also a class of studies that have focused on the integrated scheduling of thermostatically controlled household loads such as air conditioners and water heaters [23,24]. However, these studies are limited to centralized house/water temperature control.

Few studies have addressed integrated household appliances scheduling and PV aggregation by the aggregator. Authors in [25] have developed a resource allocation method for customer assets in which the goal of aggregator is finding an incentive pricing vector that can persuade customers to allow aggregator control their loads. However, customers are still decision-makers to have each of their loads scheduled with the offered price by aggregator or to pay the utility company prices. In [26], a distributed multi-residential scheduling algorithm is proposed in which every residence tries to find a schedule that maximizes its own satisfaction level defined as utility minus cost while respecting its consumption limit calculated by the aggregator for each residence. Authors in [27] developed an automated scheduling for renewable energy system in order to address the power imbalance and meet customers demands. studied a problem of roof-top PVs and wind integration. However, an integrated load scheduling approach looking at several prosumers' flexibility and renewable energy aggregation potential as a considerable amount of bidding power is still uninvestigated.

On the other hand, to maximize customers satisfaction level in a multi-prosumer framework, *fairness* should be addressed which is rarely discussed in the previous related studies. In [28] an auction-based incentive mechanism for emergency demand response is proposed that guarantees users receive similar reward for similar load reduction. In [29] a centralized scheduler first solves the optimization problem then, using the Shapely Value concept in game theory, fairness is implemented in a smart billing mechanism that ensures users would be charged based on the impact of their loads on the total system cost. It is of note that in the above studies, fairness is not addressed in the scheduling process. Authors in [30] have proposed a method employing water-filling scheduling algorithm which allocates loads to low-priced time slots until a flat power usage profile is achieved; fairness is defined as equal inconvenience meaning that load time changes among all customers is relatively the same after scheduling. A rationality scheduling strategy in integrated distribution network is proposed by [31] in which the recovery of loads is implemented with different scheduling priorities.

Technical communication aspects, privacy preserving and cloud-based information exchange between aggregators and WiFi-enabled smart appliances through Internet of Things (IoT) are addressed in the previous studies [32–35].

To the best of our knowledge, the literature lacks an integrated smart appliances scheduling and renewable energy aggregation for a large number of prosumers in a fair manner. In this paper, a multi-prosumer framework is designed in which smart appliances are directly scheduled by the aggregator and surplus generations of large-scale residential PVs are aggregated. Under this framework, a fair rewarding system is developed leading to a fair selection among all customers to shift smart appliances while not compromising their comfort.

The problem of consumers and demand response aggregators collaboration is modeled as a multi-objective optimization problem in several studies [36–39]. These studies have defined conflicting objectives for consumers and the aggregator in order to reach a trade-off between their objectives. For instance, while the aggregator's objective is to maximize its payoff, the consumers' objective is to minimize the waiting time for the operation of appliances or to maximize their social welfare defined as the difference between the modified and the reference consumption. However, in this paper, we do not measure the user's convenience by social welfare or operation delay for the appliances. Here, the aggregator's goal is to maximize its profit while remaining committed to the user-defined flexibility interval in shifting smart appliances and fairly compensating consumers based on the number of their incorporated appliances.

The major contributions of this paper are summarized as follows.

1. A new large-scale multi-prosumer framework is introduced for directly re-scheduling residential smart appliances and aggregating surplus generation of PVs by a single aggregator for bidding in the wholesale market. The capacity of load flexibility and prompt availability of smart appliances are utilized as well as the excess solar power generation when batteries are not available.
2. A fair selection approach is employed as a rewarding system in the scheduling algorithm. The rewarding system enforces aggregator to have fair selections of appliances for shifting among residences while it also respects their predefined time frames in the shifts.
3. Because of np-hard nature of the problem and to overcome the time-complexity, a heuristic algorithm is devised which produces near-optimal results with a very small gap with the optimal result. The short execution time of the devised heuristic algorithm improves the scalability of the problem.

The remainder of this paper is organized as follows. In Section "Multi-prosumer framework and system model", a detailed description of the proposed framework is provided. Also customers load flexibility and problem components are described and modeled in this section. The proposed model for integrated scheduling of appliances in multi-prosumer framework is formulated in Section "Multi-prosumer load scheduling". It will be followed in Section "Numerical studies", with approaches in solving the problem, numerical studies and simulation results. Finally, conclusion and future research key points are presented in Section "Conclusion".

Multi-prosumer framework and system model

Multi-prosumer framework

In the proposed framework, we consider an Independent System Operator (ISO), a single aggregator and a set of residences, Fig.1. The aggregator has an Integrated Scheduling Unit through which it directly communicates with smart appliances inside the participant residences and their rooftop PV panels. In order to reach the minimum bidding power, the Integrated Scheduling Unit finds an efficient overall reschedule for all smart appliances and calculates surplus generation of PVs after supplying the electricity needed by non-shiftable appliances. Then, directly executes the rescheduling program with all smart appliances in the residences. The aggregator via its Market Communication Unit submits its DR offer in the wholesale market for trading. On the other hand, every residence may have its own Household Scheduling Device (HSD) for initial energy consumption scheduling based on preferred start times and time-of-use prices.

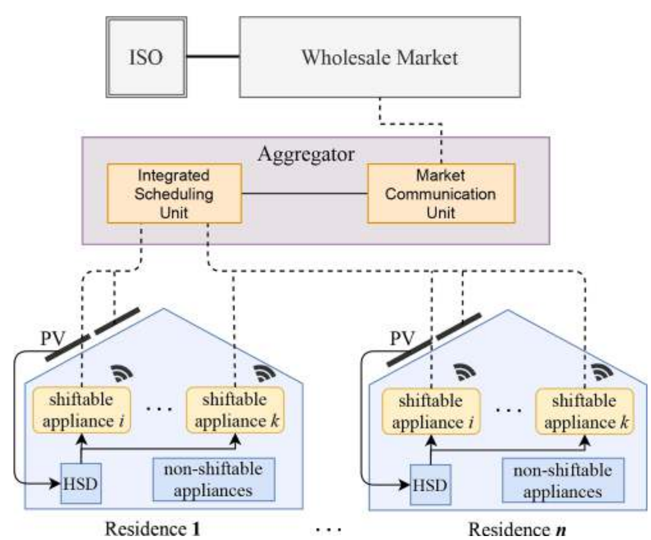

Fig. 1. Architecture and communication of the aggregator in multi-prosumer framework.

System model

Appliances

In this model, each participating residence has a number of shiftable smart appliances with flexible operating time. Aggregator sends operation commands directly to the appliances if they are selected to be rescheduled. Each participating residence h has a number of smart shiftable appliances and a number of non-shiftable appliances. Examples of smart shiftable appliances are washer, drier and dish washer that their operating time can be postponed to a later point in time or shifted to an earlier time. The studied time horizon T for scheduling consists of a number of equal timeslots. For each smart appliance, we define a demand vector specifying the number of operating timeslots and its associated power demand per operating timeslot. It is assumed that participating residences specify a pre-scheduled (preferred) start time for each of their smart shiftable appliances. Appliances are operated in customer preferred timeslots if not selected to reschedule by aggregator. Based on preferred timeslots, the demand vector for each smart appliance i in residence h is modeled as:

$$d_{i,h} = \left[d^1_{i,h}, d^2_{i,h}, \ldots, d^T_{i,h}\right], \quad \forall i \in I, \forall h \in H \tag{1}$$

where $d^t_{i,h}$ is the power demand of smart shiftable appliance i in residence h during timeslot t.

For being rescheduled by aggregator, an authorized window for the operating time of each smart appliance has to be specified by participating residences which is in the form of an $EST_{i,h}$ and a $LFT_{i,h}$ which are earliest authorized start time for smart appliance i in residence h and latest authorized finish time for smart appliance i in residence h, respectively. We also, define an authorization vector based on the above-mentioned parameters for each smart shiftable appliance i in residence h during timeslot t:

$$a_{i,h} = \left[a^1_{i,h}, a^2_{i,h}, \ldots, a^T_{i,h}\right], \quad \forall i \in I, \forall h \in H \tag{2}$$

$$a^t_{i,h} = \begin{cases} 1 & \text{if } EST_{i,h} \leqslant t \leqslant LFT_{i,h} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where constraint (3) ensures that authorization value of appliance i in residence h at timeslot t equals 1 if this timeslot falls within user-specified time limits and equals 0 otherwise.

Similarly, for non-shiftable appliances, the power demand vector for all non-shiftables appliances in residence h is defined as:

$$c_h = \left[c^1_h, c^2_h, \ldots, c^T_h\right], \quad \forall h \in H \tag{4}$$

where c^t_h is the total power demand of all non-shiftable appliances in residence h during timeslot t.

PVs

In this model, each participating residence may install and use its own solar PV system. A PV array, on a house's ground or on the rooftop of a household, is installed to independently supply a certain amount of power for household electricity demand. It is assumed that the aggregator prioritizes the using of excess energy of solar panels in residences over rescheduling smart appliances for reaching the bidding size. The output power of a household's PV array is highly affected by different weather conditions. Solar intermittency and changing irradiance causes fluctuations in power generation and lowers the level of power penetration. Authors in [40], using beta distribution, have modeled the solar radiation probability function. The output power of a PV as a radiation function is defined as radiation-power curve [41]. Based on this, we define the generated power by PV panel j in residence h during timeslot t as below:

$$P^t_{pv_{j,h}} = \begin{cases} Pr_{pv_{j,h}}\left(\dfrac{(R^t)^2}{R_C \cdot R_S}\right) & \text{if } 0 \leqslant R^t < R_C \\ Pr_{pv_{j,h}}\left(\dfrac{R^t}{R_S}\right) & \text{if } R_C \leqslant R^t < R_S \\ Pr_{pv_{j,h}} & \text{if } R_S \leqslant R^t \end{cases} \tag{5}$$

where $Pr_{pv_{j,h}}$ is the rated power of PV panel j in residence h, R^t is solar irradiance in timeslot t, and R_C and R_S are certain radiation point and solar radiation in the standard conditions, respectively.

Aggregator

Aggregators can be retailers, producers or independent agents in the smart grid. They collect an specified amount of energy over certain time intervals from their affiliated customers and trade it in the wholesale energy market in order to earn profits. Energy market can be an open market over various timescales or a private agreement between energy sellers and energy buyers, such as day-ahead market and real-time balancing market. Aggregators should be able to provide compelling offers to costumers in order to persuade them to participate in DR programs [19]. To this end, aggregators should consider many factors regarding both their own and their customers' concerns. In this framework, we consider one aggregator as an independent intermediary between the appliances in affiliated residential customers and the wholesale energy market. The aggregator motivates customers to participate in its DR program by providing financial rewards as compensation for rescheduling their appliances and utilizes a fair appliance selection approach for the integrated scheduling. We assume that the aggregator in order to be able to trade in the wholesale market, needs to reach bidding size, a certain amount of energy reduction Θ, from its customers' load reduction capacity and utilizing surplus PVs generations. This amount can be an accepted bid or an entrance bidding power requirement of the wholesale market. Load reduction can be achieved from rescheduling smart shiftable appliances to off-peak intervals and/or from sending excess power generated by residential PVs during peak-time interval. For rescheduling process, the aggregator performs *load reduction* and *load restoration* to shift any appliance from its pre-scheduled timeslots to off-peak timeslots. We have formulated the load reduction and the load restoration for each smart appliance i in residence h in (6) and (7). Moreover, the total reduced load and the total restored load from shifting all smart appliances are presented as $L_{rd_{sh}}$ and L_{rs} in (8) and (9), respectively.

$$LR_{i,h} = \begin{cases} \sum_{t=PST_{i,h}}^{PST_{i,h}+K_{i,h}-1} d^t_{i,h} \cdot x_{i,h} & \text{if } t \in TP \\ 0 & \text{otherwise} \end{cases} \quad \forall i \in I, \forall h \in H \tag{6}$$

where $TP = \{t \in T |\ t_{bp} \leqslant t \leqslant t_{ep}\}$

$$LS_{i,h} = \begin{cases} \sum_{t=t'}^{t'+K_{i,h}-1} d^t_{i,h} \cdot x_{i,h} & \text{if } \forall t,\ a^t_{i,h} > 0\ \&\ t \in TO \\ 0 & \text{otherwise} \end{cases} \quad \forall i \in I, \forall h \in H \tag{7}$$

where $TO = \{t \in T |\ t < t_{bp}\ \ or\ \ t > t_{ep}\}$

$$L_{rd_{sh}} = \sum_{i \in I} LR_{i,h} \tag{8}$$

$$L_{rs} = \sum_{i \in I} LS_{i,h} \tag{9}$$

where $d_{i,h}^t$ is the power demand of smart shiftable appliance i in residence h during timeslot t, $a_{i,h}^t$ is a binary variable that specifies if timeslot t is an authorized timeslot for restoring smart appliance i in residence h and $x_{i,h}$ is a binary variable specifying whether smart appliance i in residence h is shifted by the aggregator or not.

$$LR_{i,h} - LS_{i,h} = 0 \quad \forall i \in I, \forall h \in H \tag{10}$$

Constraint (10) guarantees that every reduced load from peak-time interval will be restored during off-peak hours.

Furthermore, the total generated power of all PV panels in residence h during timeslot t is defined as:

$$G_h^t = \sum_{j \in J} \left(P_{pv_{j,h}}^t \right) \quad \forall t \in T, \forall h \in H \tag{11}$$

where $P_{pv_{j,h}}^t$ is the generated power by PV panel j in residence h during timeslot t. In addition, the total load reduction attained from all PVs' excess generated power in timeslot t and the overall reduced load during peak-time interval coming from all PVs are formulated in (12) and (13), respectively.

$$L_{rd_{pv}}^t = \sum_{h \in H} \left(G_h^t - c_h^t \right) y_h \quad \forall t \in \left\{ t \in T | t_{bp} \leqslant t \leqslant t_{ep} \right\} \tag{12}$$

$$L_{rd_{pv}} = \sum_{t=t_{bp}}^{t_{ep}} L_{rd_{pv}}^t \tag{13}$$

where c_h^t is the total power demand of all non-shiftable electrical appliances in residence h during timeslot t and y_h is a binary variable specifying whether the excess generated power of PVs in residence h is utilized by aggregator or not.

In (14) the aggregator's revenue from household h based on the market price after paying PV extra generation rewards to the customers, is presented.

$$RN_h = \sum_{t=t_{bp}}^{t_{ep}} \left(G_h^t - c_h^t \right) \lambda^t - PV_{Rew} \tag{14}$$

where PV_{Rew} is the constant reward that aggregator pays to the customer in case of utilizing its PVs extra generation.

$$L_{rd_{pv}} + L_{rd_{sh}} \leqslant \Theta \tag{15}$$

Constraint (15) ensures that aggregator will perform load reduction by rescheduling smart appliances and utilizing excess power generated by PVs until it meets the total required amount of energy reduction.

Multi-prosumer load scheduling

Mathematical model

The problem of multi-prosumer integrated scheduling is studied in this section. Aggregator's goal is to maximize its profit in providing a certain amount of load reduction during peak-time while compensating its customers in a fair way. The profit of aggregator comes from utilizing excess generated power of PVs and shifting smart appliances from peak-time interval with higher market prices to off-peak intervals with lower market prices. To this end, first we define cost function for shifting a smart appliance. We assume that aggregator uses a time-of-use forecast of the wholesale market prices for its decisions. The cost of load reduction and the cost of load restoration in the best possible timeslots for smart appliance i in residence h are formulated in (16) and (17), respectively.

$$CR_{i,h} = \sum_{t=PST_{i,h}}^{PST_{i,h}+K_{i,h}-1} d_{i,h}^t \cdot \lambda^t \quad \forall i \in I, \forall h \in H \tag{16}$$

$$CS_{i,h} = \min_{t \in TO} \left\{ \sum_{t=t'}^{t'+K_{i,h}-1} d_{i,h}^t \cdot \lambda^t \;\middle|\; \forall t,\ a_{i,h}^t > 0 \right\} \quad \forall i \in I, \quad \forall h \in H \tag{17}$$

where $TO = \{t \in T | \; t < t_{bp} \;\; or \;\; t > t_{ep}\}$ and λ^t is the wholesale market price for power consumption in timeslot t.

$$CR_{i,h} - CS_{i,h} > 0 \quad \forall i \in I, \forall h \in H \tag{18}$$

Constraint (18) guarantees that shifting each smart appliance is a cost effective action.

In (19), we have formulated the optimization problem for overall profit of aggregator in the proposed multi-prosumer framework.

$$\begin{aligned}
\max_{x_{i,h}, y_h, N_h} \quad & \sum_{h \in H} (RN_h) y_h + \sum_{i \in I} \left(CR_{i,h} - CS_{i,h} - \eta_{i,h} \right) x_{i,h} \\
\text{s.t.} \quad & LR_{i,h} - LS_{i,h} = 0, \quad \forall i \in I, \forall h \in H \\
& CR_{i,h} - CS_{i,h} > 0, \quad \forall i \in I, \forall h \in H \\
& L_{rd_{pv}} + L_{rd_{sh}} \leqslant \Theta, \\
& \eta_{i,h} = SH_{Rew} + W \cdot N_h, \\
& x_{i,h} \in \{0,1\}, \\
& y_h \in \{0,1\}, \\
& N_h \in \{0,1,2,\ldots,z\}
\end{aligned} \tag{19}$$

In the following, fairness constraint (20) in selection approach of the aggregator will be discussed.

$$\eta_{i,h} = SH_{Rew} + W \cdot N_h \tag{20}$$

The aggregator pays a base reward SH_{Rew} as compensation for shifting the first smart appliance in a residence. To ensure that the selection is fair and not biased toward specific residences, the aggregator either selects the next candidate from other residences or pays a greater reward for selecting other appliances to shift from the same residence. To this end, we have considered an associated weight for the reward calculation for each residence which increases by an arithmetic growth rate after each appliance selection from a particular residence. Assuming W as a constant weight for reward growth and N_h as the number of appliances in residence h already shifted by the aggregator, $W \times N_h$ produces a range of growing rewards for shifting smart appliances in each residence h. Therefore, $\eta_{i,h}$ which is the financial reward that the aggregator pays for shifting appliance i in residence h depends on the number of previously shifted appliances in the same residence. This constraint produces a greater overall reward when appliances for shifting are selected from one residence compared with selecting appliances from two different residences. Finally, since the aggregator tries not to pay extra financial rewards to customers in order to maximize its profit, fairness in selection is enforced to the rescheduling approach of the aggregator.

Moreover, since forecasting whole sale market prices are inherently

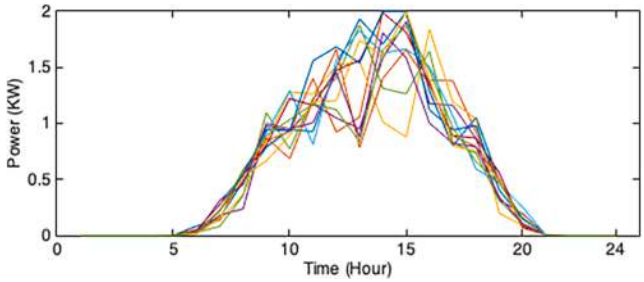

Fig. 2. The scenarios for solar panels generation in a PV-equipped residence.

uncertain, we considered uncertainty for the time-of-use forecast of the prices. To deal with uncertain data, an appropriate probabilistic approach has to be employed. Using a forecast price vector without considering uncertainty is unreliable and would increase the risk for the aggregator's benefit. There are a variety of possible wholesale market prices in each time horizon. The daily and hourly variations of the wholesale prices are due to the role of market players, consumers' power consumption behaviors and the impact of renewable energy which in turn depends on the weather condition. To have a reliable price forecast vector, the probabilistic approach can be used for generating a number of scenarios of wholesale market prices derived from historical data and using normal distribution function to deal with its associated uncertainty [42,43]. The probability density function for market prices based on [44] is given in (21).

$$f(X^t) = \frac{1}{\sigma_s\sqrt{2\pi}} exp(-\frac{(X^t-\mu_s)^2}{2\sigma_s^2}) \qquad \forall t \in T \tag{21}$$

where X^t is the predicted market price for timeslot t, and μ_s and σ_s^2 are mean and variance for price scenarios in timeslot t, respectively.

The uncertainty in solar power generation by the prosumers is also included in the system model using a scenario-based approach. To this end, we consider historical data of radiation samples and after generating each scenario, we calculate the expected value for the output power of PV panels in each residence based on mean value and standard deviation in probability distribution function. In this way, different states are considered through various scenarios and the system under these scenarios analyzed as a deterministic input [45]. Fig. 2 represents the produced scenarios for the solar panels output power in a PV-equipped residence.

In the following section, we will describe our approaches to solve the optimization problem in detail.

The solving approaches

The model presented in (19) is an ILP (Integer Linear Programming) optimization problem. Regarding the larger size of loads from PVs' extra generations compared to the shiftable loads and since utilizing these loads by aggregator would not jeopardize customer's comfort, we prioritize utilizing PVs for the aggregator's load reduction goal. Therefore, we divide the optimization problem into two steps. First, the aggregator utilizes all households PVs extra generation and subtracts it from the total required amount of load reduction Θ. In the next step, the aggregator goes through shifting loads from peak hours to off-peak hours in order to fulfill its required load reduction. Thus, the total required amount of load reduction from shifting smart appliances is defined as:

$$\Theta_r = \Theta - L_{rd_{pv}} \tag{22}$$

where Θ_r is the total required amount of energy reduction after utilizing all PVs' extra generations. Considering this notion, below we rewrite a simplified optimization problem assuming that the first step is calculated:

$$\begin{aligned}
\max_{x_{i,h},N_h} \quad & \sum_{i\in I}(CR_{i,h}-CS_{i,h}-\eta_{i,h})x_{i,h} \\
\text{s.t.} \quad & LR_{i,h}-LS_{i,h}=0, \qquad \forall i\in I, \forall h \in H \\
& CR_{i,h}-CS_{i,h}>0, \qquad \forall i\in I, \forall h \in H \\
& L_{rd_{sh}} \leqslant \Theta_r, \\
& \eta_{i,h} = SH_{Rew} + W\cdot N_h, \\
& x_{i,h}\in\{0,1\}, \\
& N_h \in \{0,1,2,\ldots,z\}
\end{aligned} \tag{23}$$

Here, we consider each appliance with the operating time in peak-time interval as an item and its associated load as weight of the item. We further consider the aggregator's earning from shifting an appliance as value of the item (i.e. the difference between the cost of load reduction and the cost of load restoration minus payable reward to the customer). Then, regardless of the fairness constraint, the problem is analogous to the classical 0–1 Knapsack Problem where the total required load reduction could be viewed as capacity of the knapsack. The 0–1 knapsack problem is defined as filling a fixed-size capacity knapsack by choosing from a set of items, each associated with a weight and value such that the overall knapsack value is maximized. The Knapsack Problem is one of the well-known NP-hard problems [46–48]. Although for some instances of knapsack problem polynomial-time approximation algorithms are proposed based on Dynamic Programming and Branch and Bound, there are knapsack instances that are hard to solve; Such as when size of the problem is very large [49], weights and values of the items are strongly correlated [50,51] and weights and values are rational numbers [52]; that are all the features of the problem we study here. In addition, fairness in knapsack problem has recently been addressed. Authors in [53] have defined a group fairness notation for the knapsack problem such that the goal is to maximize the overall value of the knapsack while items from each group/category are presented in the knapsack in a fair way. To ensure fairness among all groups, they have defined a bound/limit on weight, value and number of items from each group one at a time and have proposed algorithms for each problem individually. However, the fairness notation used in the above work is different in concept with what we have in this study. Here, defining an upper bound on the number of shifted appliances from each residence may make customers with more interest in contribution feel unmotivated. We implement fairness among residences as a part of a rewarding system. In this way, customers are motivated to participate with more appliances and with more flexible time frames to receive increasing rewards.

In the following, a heuristic algorithm for the optimization problem in (23) is presented. Our devised heuristic algorithm is similar to greedy approach for knapsack problem while it is technically different in additional features. It has a good performance guarantee and provides the approximate solution in an ideal running time. To this end, we sort the items (smart appliances with the operating time in peak-time interval) in a decreasing order of value-per-load ratio. The value-per-load ratio is defined as $(CR_{i,h}-CS_{i,h}-\eta_{i,h})/LR_{i,h}$ which is what the aggregator earns from shifting an item i per amount of the load. Since, at the beginning N_h is equal to 0 for all households, $\eta_{i,h}$ for all of the items is equal to base reward SH_{Rew} initially. Then, the aggregator removes items one-by-one from the ordered list. After each removal algorithm must recalculate the value-per-load for the remaining *dependent* appliances in the list which belong to the same household. Therefore, the list needs to be re-sorted after each removal by the aggragator. Sorting the list after each removal leads to n times sorting the list which impose an additional time-complexity $O(n^2 logn)$ to the algorithm. Assuming that the weight for increasing rewards is relatively small compared to the value of the items, we locally re-locate dependent items with the updated value instead of globally sorting the whole list. To this end, we move down each dependent item until it reaches an item smaller than itself (its proper position). Thus, the time-complexity would depend on the number of comparisons needed for relocating each dependent item.

However, even in the worst case scenario, it helps reducing running time significantly since we are using Straight Insertion Sort concept on a very nearly sorted list [54]. The devised Heuristic Fair Scheduling (HFS) algorithm is presented in more detail in Algorithm 1.

Algorithm 1
Heuristic Fair Scheduling, HFS

input : Households set H, Smart appliances set I, Shiftables vector $d_{i,h}$, authorization vector $a_{i,h}$, Non-shiftables vector c_h, Bidding power Θ, Total generated power G_h.
output: Set of S_i, S_h
//Initialization $S_h \leftarrow \emptyset$, $S_i \leftarrow \emptyset$
for *each residence*, $h \in H$ **do**
  for *each timeslot in peak-time interval*, $t \in TP$ **do**
    $EG_h \leftarrow (G_h^t - c_h^t)$ //Calc PVs extra gen
  end
  if $EG_h > 0$ **then**
    $L_{rd_{pv}} \leftarrow L_{rd_{pv}} + EG_h$
    $\eta_h \leftarrow (\eta_h + PV_{Rew})$, $S_h \leftarrow S_h \cup \{h_i\}$
  end
end
$\theta_r \leftarrow (\theta - L_{rd_{pv}})$
for *each appliance*, $i \in I$ **do**
  if $LR_{i,h} \neq 0$ & $LS_{i,h} \neq 0$ **then**
    $Gain_i \leftarrow (CR_{i,h} - CS_{i,h} - \eta_{i,h})$
    //Calculate *Value-per-Load*
    $VL_i \leftarrow (Gain_i / LR_{i,h})$
  end
  else
    $VL_i \leftarrow 0$
  end
end
$List_i$=Sort-Descending (VL_i)
//for all $i \in List_i$ while $VL_i \geq 0$
if $LR_{i,h} \leq \theta_r$ **then**
  $\theta_r \leftarrow (\theta_r - LR_{i,h})$
  $L_{rd_{sh}} \leftarrow L_{rd_{sh}} + LR_{i,h}$
  $\eta_{i,h} \leftarrow \eta_{i,h} + SH_{rew}$, $t_i \leftarrow t'_i$, $S_i \leftarrow S_i \cup \{i\}$
  // *re-locating dependants*
  for *all depend appliances in h*, $dp \in I$ **do**
    if $Gain_{dp} \geq 0$ **then**
      $Gain_{dp} \leftarrow Gain_{dp} - W$
      $VL_{dp} \leftarrow (Gain_{dp} / LR_{dp,h})$
    else
      $VL_{dp} \leftarrow 0$
    end
    while $VL_{dp} < VL_{dp+1}$ & $dp \leq I$ **do**
      $swap(VL_{dp}, VL_{dp+1})$
    end
  end
end
end
return (S_i, S_h)

In the following, we analyze the performance of our devised HFS algorithm. For this purpose, first we study the proof of how a greedy knapsack algorithm with items sorted based on value-per-weight is a 1/2-approximation algorithm and guarantees to give at least 1/2 of the optimal value [55,56]. The greedy algorithm for knapsack picks items which are sorted by non-increasing order of $value_i/weight_i$ until it reaches an item that does not fit in knapsack. If we consider a refinement to the greedy algorithm such that the algorithm picks either all of the first k items or the single item $k+1$ that does not fit in, which ever has a greater value. Using the concept of fractional knapsack problem [57], if we are allowed to use a fraction of only the last item $k+1$ to fill the knapsack fully, that would give us the maximum possible value which is greater or equal to the optimal value for non-fractional knapsack. Considering this refinement, the value for greedy algorithm is greater than or equal to sum of the values of first k items while also it is greater than or equal to the value of item $k+1$. By adding two inequalities and simplifying it, the value of refined greedy algorithm is greater than or equal to 1/2 of the total value of the first $k+1$ items which is better than the fractional result. Furthermore, the value of the refined greedy algorithm is at least 1/2 of the optimal value [56]. Now, regarding HFS algorithm we suppose that the load of each smart shiftable appliance is very small compared to the total required amount of load reduction such that:

$$LR_{i,h} \leqslant 0.05\ \Theta_r, \quad \forall i \in I, \forall h \in H \tag{24}$$

In this way, if the algorithms does not pick all the items and the item $k+1$ overloads the required amount of load reduction, surely only 5% of Θ_r is remained while the items already picked are the most valuable ones. So, the value of the algorithm is greater than or equal to 95% of the value of fractional algorithm and is also greater than or equal to 95% of the optimal value. Therefore, the devised HFS algorithm's result is at least 0.95 of the optimal solution. Note that it is assumed that the weight W for increasing rewards is relatively small compared to the value of the items. So, re-locating dependents does not have any significant effect on the accuracy of the approximation.

Numerical studies

In this section, the simulation results in real world scenarios are presented to evaluate the proposed model. To investigate the effectiveness of the proposed multi-prosumer framework, two large-scale multi-prosumer case studies are designed. Both case studies consist of one aggregator and 5000 residences with multiple non-shiftable and smart shiftable appliances in each residence. Three types of smart shiftable appliances are considered for scheduling including washing machine, clothes dryer and dish washer. The real consumption data of cycles and operating time of appliances are obtained from the UK Department of Energy and Climate Change data tables [58] which are then normalized and randomly distributed in a 24-h period. It is also assumed that 66.7 percent of consumers' households are equipped with PV panels. The power generated by PVs is primarily used by household's non-shiftable electrical appliances and excess generated power of PVs in high-price interval will be managed by the aggregator.

The rescheduling interval is 24-h divided by 1-h timeslots. The real-time hourly market prices from the ComEd in October 2017 are utilized in the simulations. High-price interval is assumed to be [15:00–20:00] in the studied prices and the remaining of the 24-h interval is considered low-price. The wholesale market prices are depicted in Fig. 3 and the high-price interval is highlighted in red.

The aggregator must meet the required amount of load reduction specified by the bidding power to be able to trade in the wholesale market. We assigned a slightly greater value than the defined bidding power to the variable Θ to ensure that aggregator meets the minimum requirement of the wholesale market. All the simulations are performed using MATLAB R2015a on a 1.6 GHz Dual-Core Intel Core i5 processor with 8 GB of DDR3 RAM.

In the following, we investigate the advantages of our proposed

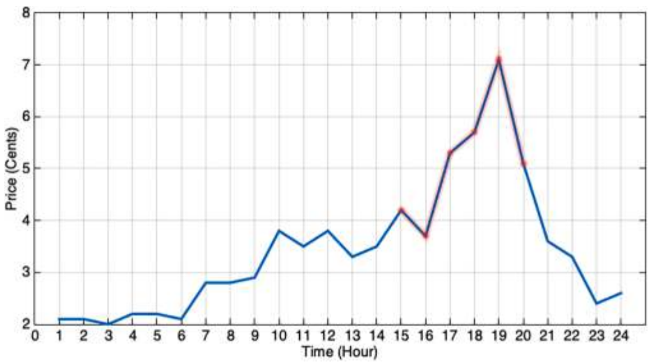

Fig. 3. Wholesale market prices for a Fall day.

multi-prosumer framework and how it affects households savings, load curve correction and aggregator's profit. Also, while obtaining the optimal result in large-scale is impractical in polynomial time, we showed in the previous section that our devised HFS algorithm's near-optimal result is very close to the optimal with only %5 gap. To show the performance of our algorithm, we have also compared the result of the HFS algorithm with the result from Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) methods. PSO, in brief, is an evolutionary algorithm proposed by Kennedy and Eberhart [59] which simulates the social behavior of fish schooling or bird flocking. In this method, each solution is called a particle and a swarm of particles searches the problem space. Then, regarding the direction of the flying track, each particle updates itself and finds the best solution. The global best solution will be generated by the whole swarm. Genetic Algorithm, on the other hand, is a computation method that emulates biological evolution. It maps an optimization problem to a set of strings of potential solutions. Then, the most promising string will be chosen to be manipulated by the genetic operator and for producing a new population to improve the solution [60]. In this study, we have considered 10 particles and 20 iterations for solving the problem using PSO and GA methods.

Case I

In the first case study, customers have pre-scheduled their smart appliances to be operated during [8:00–24:00]. It is considered that aggregator's re-scheduling interval begins at $5:00$ *am*. The minimum bidding power for the aggregator is assumed to be 11 MW.

Results of running the case with PSO and GA shows that the profit of $242.6 and $242.2 is achieved for the aggregator by shifting 6837 and 6834 loads respectively and by using the excess generation of PVs during the high-price interval. The aggregator's revenue of shifting appliances is calculated by revenue of load reduction performed between 15:00 and 20:00 subtracted by the total amount paid to the customers as shift rewards. Note that, all the shifts are performed within the customers' predefined convenience times which was assigned to each load.

By solving the case study using our developed HFS algorithm, 6724 total loads are shifted from high-price interval and the aggregator earned $262.01 as profit. In comparison with the PSO and the GA results, aggregator earned more profit while less customer appliances are shifted for reaching to the same amount of bidding power. The HFS algorithm also outperformed other methods significantly in terms of the running time as it took 28.8 s to reach a near-optimal result. Figs. 4–6 demonstrate the impact of rescheduling of smart appliances on the load distribution by the PSO, the GA and the HFS algorithm, respectively. It is shown how the overall consumption pattern of smart appliances has changed after rescheduling performed by each algorithm.

Total power generation by PV-equipped residences and total demand of non-shiftable appliances for the same residences are depicted in Fig. 7. Aggregator, during high-price interval, aggregates and utilizes what remains from generation of PVs in each residence after the

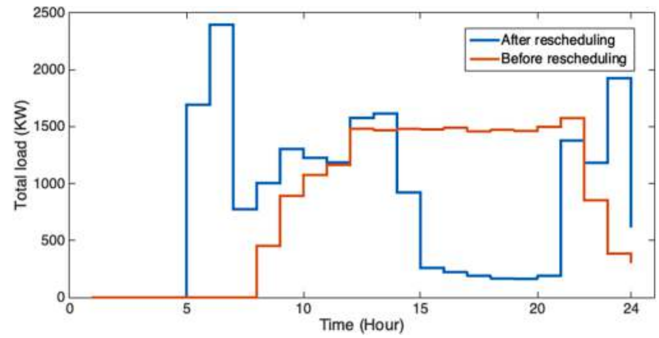

Fig. 4. Case I; The impact of rescheduling on the smart appliances' total load curve [Result of the PSO].

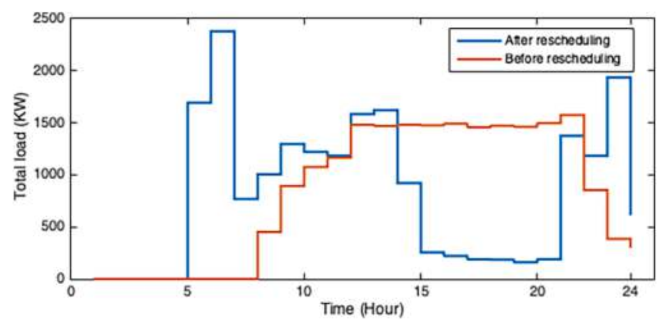

Fig. 5. Case I; The impact of rescheduling on the smart appliances' total load curve [Result of the GA].

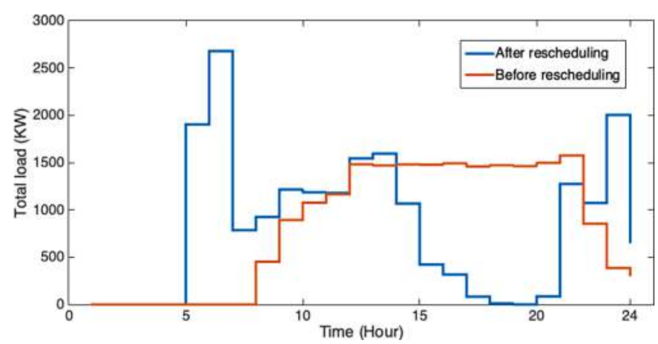

Fig. 6. Case I; The impact of rescheduling on the smart appliances' total load curve [Result of the HFS algorithm].

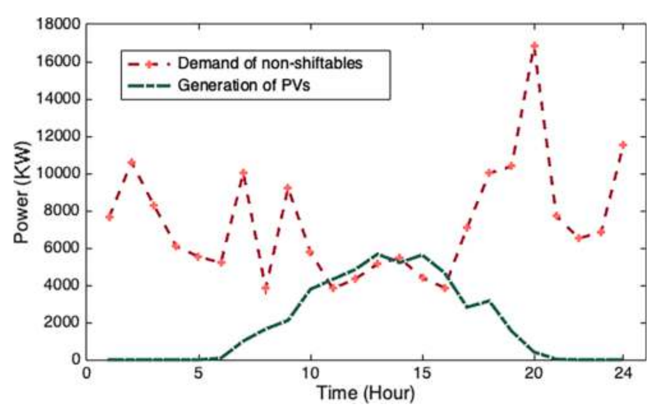

Fig. 7. The difference of generated power by all PVs and the total demand of non-shiftable appliances.

demands of its non-shiftable appliances are met.

Case II

For the second case, the minimum bidding power for the aggregator is assumed to be 12 MW to enter the wholesale market. Customers smart appliances load are pre-distributed in [12:00–24:00] and aggregator's re-scheduling interval is assumed to begin at 6 : 00 *am*.

By solving the case study using PSO and GA methods, the profits of $241.74 and $241.72 are earned by the aggregator from shifting 7607 and 7587 loads, respectively and by using the extra generation of PVs. On the other hand, after running the case study using the developed HFS algorithm, 7424 total loads are shifted from high-price interval and the aggregator earns $294.5 as profit. In addition, running time decreased significantly to as low as 48.7 s for the HFS algorithm compared to the other methods. The impact of rescheduling on the smart appliances' load curve by the PSO, the GA and the devised HFS algorithm, are depicted in Figs. 8–10, respectively.

The simulation results of PSO and GA methods and developed HFS algorithm for both case studies are summarised in Table 1. The results clearly shows that for both cases the developed HFS algorithm provides better results while it was significantly faster compared to the other methods. Also, the short execution time of the HFS algorithm would improve the scalability of the problem.

In order to investigate *fairness* of the proposed framework, we use the HFS algorithm's result for case II. Same algorithm is solved without involving the fairness constraint as well and further comparison is discussed. Impact of the fairness constraint is seen on the different amount of rewards customers receive each time for load shifting and the number of time each single residence is selected by the aggregator. These two are considered as measures used in comparison analysis. Further elaboration is as follow.

Fig. 11 represents a density diagram for the rewards that the aggregator pays to the customers for shifting each of their loads, with and without fairness constraint. This analysis shows that, without fairness, all customers received a constant reward *0.50* for each shifted appliance in their households. With fairness, on the contrary, customers with more selected appliances earned 25 to 50 percents more reward for their participation.

Fig. 12, shows how many times a single residence is selected for shift, with and without fairness constraint. In the fair approach, the number of *three-time-selected* residences has fallen indicating that the aggregator tries to avoid choosing appliances of a residence for the third time. Likewise, the number of *not selected* residences has fallen in the fair approach which means that in the aggregator's overall schedule, more appliances from the previously *not selected* residences are included compared to the unfair approach. In addition, the number of *one-time-selected* residences has increased in the fair approach. Note that, the aggregator tries to have more non-repetitive residence selections to ensure fairness, while its primary goals are reaching a required amount of load reduction, meeting costumers' convenience periods and maximizing its profit.

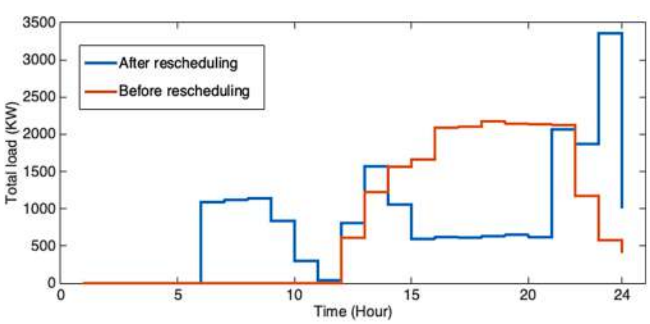

Fig. 8. Case II; The impact of rescheduling on the smart appliances' total load curve [Result of the PSO].

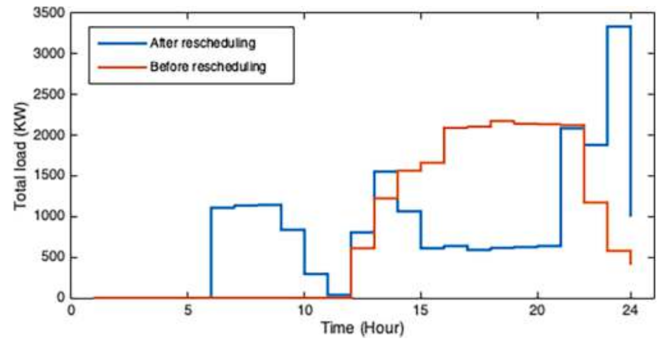

Fig. 9. Case II; The impact of rescheduling on the smart appliances' total load curve [Result of the GA].

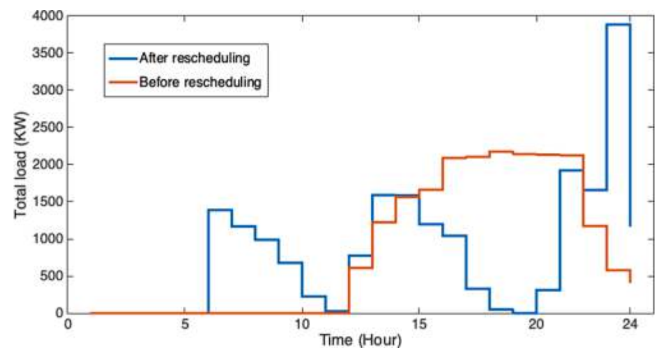

Fig. 10. Case II; The impact of rescheduling on the smart appliances' total load curve [Result of the HFS algorithm].

Table 1
Comparison between the PSO, the GA and the devised HFS algorithm for both case studies.

	Case I			Case II		
	PSO	GA	HFS	PSO	GA	HFS
Aggregator profit ($)	242.60	242.22	262.01	241.74	241.72	294.5
Total rescheduled loads	6837	6834	6724	7607	7587	7424
Total Customers reward ($) [PVs]	13.2	13.2	13.2	13.3	13.3	13.3
Total Customers reward ($) [shift]	42.5	42.42	41.2	49.21	49.27	45.2
CPU time (sec)	4523.71	5608.34	28.79	4776.48	5819.11	48.68

Conclusion

This paper studies the potentials of multi-prosumer load aggregation as a DR program. A new integrated appliance-level scheduling framework is introduced. The proposed model has been designed to be beneficial to both aggregator and its affiliated customers. It also considers fairness among residences for the load reduction which may help motivating consumers to have more smart appliance available for shift in each day and to be more flexible in defining their convenience time period. Since the problem is NP-hard, we devised a heuristic algorithm that yields an appropriate approximate result in a reasonable amount of time. Its significant short execution time would address the scalability

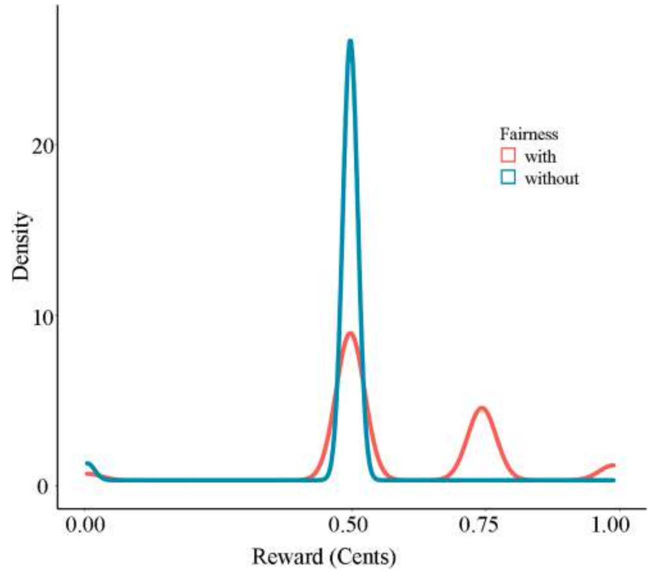

Fig. 11. The impact of fairness constraint on the customers rewards, with and without fairness.

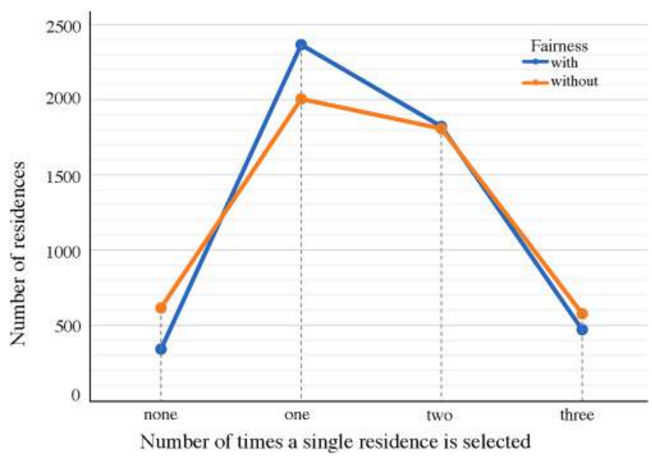

Fig. 12. The impact of fairness constraint on the residence selection, with and without fairness.

issue of the problem and make the problem more practical to be implemented in large-scale.

In this multi-prosumer framework, the aggregator provides a re-scheduling to override the predefined schedules of the selected residences while remaining committed to the customers' comfort zone. This may provide an addition to the other existing DR programs. Furthermore, since in this model, the aggregator fulfills a significant pre-specified amount of load reduction in a timely manner, it can have application in demand response events or the situations where immediate, guaranteed responses to the significant load reduction is required. We designed this framework to be useful in all wholesale markets including day-ahead and real-time market with minor modifications. Future studies can be designed to include different types of loads such as thermostatically controlled household loads like air conditioners and water heaters, in our proposed framework. In addition, investigating different fairness notions for multi-prosumer demand response seems to be an interesting area of research.

CRediT authorship contribution statement

Solmaz Moradi Moghadam: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Mahmoud Naghibzadeh:** Methodology, Supervision, Writing – review & editing, Project administration. **Modjtaba Rouhani:** Conceptualization, Formal analysis, Writing – review & editing. **Lingfeng Wang:** Conceptualization, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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