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A novel pricing scheme for managing virtual energy communities and promoting behavioral change towards energy efficiency

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ABSTRACT

The harmonization between the variable rate of energy production in the era of massive renewable energy penetration is a major challenge in an open, competitive and resilient electricity market. As a result, there is an increasing need for modern pricing schemes, which will effectively incentivize willing users to modify their energy consumption pattern to meet this objective. Current energy pricing schemes (e.g. real time pricing) treat all users the same, and do not adequately compensate for behavioral changes, thus mitigating the behavioral change dynamics. In this paper, we propose a Community Real Time Pricing (CRTP) scheme together with an Energy Community Formation Algorithm (ECFA), where users are clustered in Virtual Energy Communities (VECs) according to: (i) their level of flexibility in modifying their Energy Consumption Curve (ECC), and (ii) their relationships in Online Social Networks (OSNs), modelling peer-pressure capabilities. We show that CRTP with ECFA can simultaneously achieve considerable reduction in the system's energy cost and greater aggregated users' welfare than with the state-of-the-art real time pricing. CRTP–ECFA adopts a truly fair pricing policy, as each user is rewarded exactly according to his/her individual contribution in reducing system costs, thus promoting the desired behavioral change.

1. Introduction

The adoption of smart grid technologies and the electricity markets' liberalization are paving the way for a more efficient and green operation of electricity systems. Controllability of energy consumption facilitates penetration of renewable energy sources (RES). Moreover, innovative energy services are being offered to consumers (e.g. provision of flexibility to the grid).

Alignment between energy production with variable rate and the ad hoc energy consumption of the end users [1] requires: (i) Supply Side forecasting and Demand Side Management (DSM) tools in order to obtain the desirable aggregated ECC [2]. Current research efforts focus on pricing [3,4], which could be considered as automated DSM.

Thus, in the context of the EU-funded H2020 SOCIALENERGY project [6], we are developing a SoftWare (S/W) platform to facilitate the easy, rich and deep communication between Energy Service Provider (ESP) and its customers. In particular, the end users are able to purchase an energy program online, become part of an online social community, share knowledge and energy-related experiences with their peers, and generally enjoy a variety of innovative services that the SOCIALENERGY S/W platform provides. In this paper, we focus on the development of CRTP-ECFA by organizing users in small Virtual Energy Communities (VECs) in order to avoid the well-known problem of the "tragedy of the commons" [7], where users do not change their behavior due to the negligible impact that this change would have on their lives. CRTP-ECFA plays a critical role [11] in the behavioral dynamics of the participating users by differentiating pricing in each VEC according to the flexibility in it.

The main contributions of this paper are:

- a Community aware — Real Time Pricing (CRTP) scheme able to allow ESP to reduce system's energy cost, without sacrificing at all their quality of experience. Our results indicate very high cost reductions (10%–30%), thus illustrating CRTP's suitability for flexibility services.
- an Energy Community Formation Algorithm (ECFA) which takes into consideration both: (i) the users' ECCs, and (ii) their social interaction (relationships) in OSNs, and feeds CRTP with VECs.

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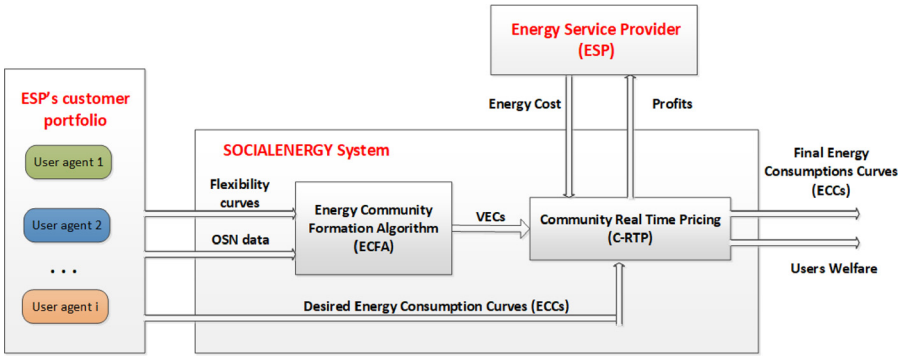

Fig. 1. Proposed system's architecture.

Table 1
Mathematical notations.

Notation	
i	End user index
k	Time slot index
c	Community index
N	Set of end users
H	Set of time slots (scheduling Horizon)
x_i^k	Actual energy consumption of user i at timeslot k
x_c^k	Actual energy consumption of community c at timeslot k
$\overline{x_i^k}$	Desired energy consumption of user i at timeslot k
$\overline{x_c^k}$	Desired energy consumption of community c at timeslot k
ω_i^k	Elasticity parameter of user i at timeslot k
$U_i^k(x_i^k)$	Utility function of user i at timeslot k
G_k	Total cost of energy (wholesale market) at timeslot k
c	Parameter of the cost function
p^k	Price per energy unit paid by the ESP to the wholesale market
p_c^k	Price per energy unit for each community c
B_i^k	Electricity bill of user i at timeslot k
B_c^k	Electricity bill of community c at timeslot k
γ	Parameter quantifying the level of incentives that CRTP provides
UW_i^k	User's Welfare of user i at timeslot k
TW	Total Welfare
$\delta_c(m)$	percentage of reduction of user i at k in the mth iteration of CRTP
w_1	trade-off between similarity in flexibility and social connections
$f(i, j)$	level of social connection between i and j
$Fr(i, j)$	expresses if i is socially connected with j
$Cf(i, j)$	number of common social connections between i and j
$Tf(i, j)$	total number of social connections between i and j
ω_pp_i	flexibility of consumer i after the community effect
max_pp	maximum peer pressure percentage affected in consumer
VEC	Virtual Energy Community
RTP	Real Time Pricing
CRTP	Community Real Time Pricing
ECFA	Energy Community Formation Algorithm
OSN	Online Social Networks
VEC	Virtual Energy Community
ECC	Energy Consumption Curve
DSM	Demand Side Management
ESP	Energy Service Provider

The rest of this work is structured as follows: Section 2 presents our system model, while Section 3 analyzes the proposed ECFA and CRTP algorithms. In Section 4, the proposed framework and algorithms are evaluated. Finally, Section 5 concludes our work.

2. Proposed system model

The ESP purchases energy from the wholesale electricity market at a time- and volume-variant cost in order to satisfy the demand of its consumers, and seeks to achieve profits not only from the retail market but also from the flexibility market [32]. Towards this end, the ESP must modify the initial aggregated Energy Consumption Curve of entire customer portfolio to an aggregated ECC that is closer to the desired (supply) curve without sacrificing the welfare (comfort derived from the consumption minus the bill that they pay) of the consumers. In order to achieve this, an automated Demand Side Management (DSM) system will be exploited in the form of an innovative pricing scheme able to extract value from the consumers' online social relationships and flexibility levels. Fig. 1 depicts a birds' eye viewand constitutes a flowchart of the two main components of the proposed framework, which are CRTP and ECFA. As depicted in Fig. 1 the ECFA module takes dynamically as input: (1) the flexibility curves of the consumers (flexibility parameter which is noted as ω in Section 3.1), which can be declared or measured from historical data, and (2) an online social network graph representing the social connections among them consumers (cf. OSN data which are defined in Section 3.6) and modelling the peer-pressure connected consumers can exert to each other. The objective of ECFA (its output) is the creation of a set of VECs/communities (noted as $C = \{c_1, c_2, ..., c_{|C|}\}$ in Section 3.6) which is done through a multi-objective spectral clustering algorithm [8,31]. The clustering algorithm aims to minimize the inter-coherency among different clusters (i.e. VECs) and simultaneously maximize the intra-coherency of the members of each single VEC) for an appropriate choice of the distance metric between consumers. From a behavioral efficiency, social dynamics and educational point of view, and based on recent findings from real-life surveys and pilots [9], it is rational to put together users with similar social connections, because this would intrinsically incentivize them to be more engaged in improving their own performance as well as help their community to achieve its objectives [10]. When the members of a VEC have strong personal relationships and continuously interact with each other by using OSNs we expect a more positive "social network synergy" effect [11,12]. The aforementioned set C is fed into the CRTP module (which is shown in the flowchart of Fig. 1 and is presented in Section 3.4) which also takes as input: (a) the energy cost at time k (which is modeled and analyzed in Section 3.2), which is itself a function of the total demand at time interval k, b) the desired Energy Consumption Curves (ECCs) of each user (for user i at time instant k is noted as $\overline{x_i^k}$ in Section 3.1). The output of the proposed CRTP is: (a) the final ECC of each user (for user i at time instant k is noted as x_i^k Section 3.1), (b) the welfare of each user (noted as UW in Section 3.3).

3. Proposed community real time framework

In this section, the mathematical modeling and the operation of ECFA and CRTP are presented. Initially in Table 1 are summarized and highlighted the mathematical notations and the acronyms that this work uses.

Then we present: (i) a widely accepted user model and a well-known energy cost model that will be used to evaluate the proposed framework, (ii) a significant pricing scheme, named Real Time Pricing (RTP),

which is the predecessor of CRTP, (iii) the proposed Community − Real Time Pricing (CRTP) scheme, (iv) the criteria for the design of ECFA according to the requirements that are derived from CRTP, and (v) the proposed novel Energy Community Formation Algorithm (ECFA). The end users (energy consumers) participating in the system form set $N = \{1,2,...,|N|\}$. In each user i it has been placed (from the user her(his) self or from her/his ESP) a smart meter, which is able to monitor her/his ECC. We consider a finite time horizon of time intervals $H = \{1, 2,...,|H|\}$. All time intervals $k \in H$ are of equal but arbitrary length. Each user i belongs to exactly one community c and the set of communities forms set C. User i has a desired energy consumption $\overline{x_i^k}$ at time interval k, which is generally different for each user and time slot. We assume that the desired consumption of user i at time k is modified to the actual consumption x_i^k, through its participation to an EP (Energy Program). The total desired and actual consumption of community c at interval k are

$$\overline{x_c^k} = \sum_{i\in c} \overline{x_i^k} \text{ and } x_c^k = \sum_{i\in c} x_i^k \tag{1}$$

3.1. User model

The convenience of user i at time interval k is expressed through her *utility function* $u_i^k(x_i^k, \omega_i^k)$. This is a function of the user's consumption x_i^k and her flexibility parameter ω_i^k. Intuitively, $u_i^k(x_i^k, \omega_i^k)$ expresses how much user i values (in monetary terms) consumption x_i^k at time k. The utility function that is used here for the evaluation of CRTP is adopted from microeconomics theory [17–20] and it is a widely accepted method for the evaluation of pricing models in smart grids [27,28]. The general form of the utility function is taken to be the same for each i, k, but parameter ω_i^k distinguishes different user and time preferences. A concave and increasing utility function of x_i^k and ω_i^k with a constant maximum value (desired consumption) after a saturation point (related to $\overline{x_i^k}$) is widely adopted; in particular, in our performance evaluation results we will take:

$$u_i^k(x_i^k, \omega_i^k) = -\omega_i^k \cdot (\overline{x_i^k} - x_i^k)^2 \tag{2}$$

Note that the utility function of user k is maximized for $x_i^k = \overline{x_i^k}$ (that's why the $\overline{x_i^k}$'s are referred to as the "desired" consumptions). For the scope of the current work and without loss of generality [15,21], we assume only one continuous, dispatchable and positive load for each user i, representing the sum of the dispatchable/curtailable consumptions of all her electric appliances at time k. Finally, we should note that the aforementioned utility function is used only for evaluation purposes (for comparing CRTP to RTP), while CRTP does not make any assumption on its form.

3.2. Energy cost model

In order to satisfy the demand of users in N, the ESP sells energy to them, which is provided by the wholesale electricity market. The cost for the ESP to buy an amount of energy equal to the total demand $\sum_{i=1}^{N} x_i^k$ in time interval k is denoted as $G_k = G\left(\sum_{i=1}^{N} x_i^k\right)$. It is natural to assume an increasing and convex (expressing economies of scale) form for G_k. In our performance evaluation section, we use a quadratic function:

$$G\left(\sum_{i=1}^{N} x_i^k\right) = c \cdot \left(\sum_{i=1}^{N} x_i^k\right)^2 \tag{3}$$

as is also widely done in the literature [16,18–21], where c is a cost parameter. We again note that the proposed framework does not make any assumption on the form of the energy cost function, and the quadratic form is used only in the performance evaluation section to compare the performance of CRTP and RTP.

3.3. Real Time Pricing (RTP)

Existing RTP models [13,16,21,25,26] calculate the prices in each time slot k through the following iterative process. Users initially set their desired consumptions. The first step is to calculate the price per energy unit that ESP pays to the wholesale market, as follows:

$$p^k = \frac{G_k}{\sum_{i=1}^{N} x_i^k} \tag{4}$$

In the second step, users adjust their consumption x_i^k as a response to the price p^k in order to maximize their welfare. The User Welfare (UW) of i is defined as:

$$UW_i^k = u_i^k(x_i^k, \omega_i^k) - p^k x_i^k \tag{5}$$

After a number of iterations between the two aforementioned steps, the system converges to the price p^k and the actual consumptions x_i^k for each user i in N that maximize the total welfare:

$$TW = \sum_{i\in N} [u_i^k(x_i^k, \omega_i^k)] - G_k. \tag{6}$$

Thus, in RTP, the energy scheduling problem at a timeslot k is defined as the use of the users' desired energy consumption and the users' utility functions in order to calculate the actual energy consumptions that minimize energy costs (G_k), while maximizing users' convenience (UW). This fact positively affects the profit margins of the ESP/retailer in the open electricity market. Finally, we should note that in this paper, we only consider energy load shedding. Modeling of energy load shifts will be part of our future work.

3.4. Community — Real Time Pricing (CRTP)

As mentioned earlier, the RTP model does not *efficiently* incentivize changes (i.e. cuts and shifts) in the ECC of the users because it does not fairly allocate the benefits obtained from these changes to the users that created them. G_k is convex. In this case the reduction of the total energy reduces the average price (integral of G_k divided by the total consumption). This is because the price of its unit of energy is the derivative of G_k. G_k is convex and has a positive second derivative. According to it the price of each unit increases (first derivative) as the total consumption increases. Thus, the same happens with the average price which is noted as p^k in Eq. (4). With RTP, the benefits of the actions of a specific user are distributed to all users proportionally to their actual consumption. In this way, a user may gain from the behavioral changes of other users, even if she did not perform any change in her behavior (ECC modification). In order to avoid this phenomenon, our proposed CRTP-ECFA framework factorizes the desired and the actual consumption of the participating users in order to enhance RTP with behavioral efficiency (see Section 1). Additionally, and in order to generate a degree of peer pressure to the participating users and increase their flexibility (modeled through parameter ω_i^k), users are grouped into communities. Thus, we are able to charge them in each time instant k according to the aggregated desired energy consumption $\overline{x_c^k}$ and the aggregated actual energy consumption x_c^k of community c. According to these, the aggregated bill B_c^k of community c for time interval k is given as

$$B_c^k = \overline{p^k}\,\overline{x_c^k} - \gamma \frac{(\overline{x_c^k} - x_c^k)}{\sum_{c\in C} (\overline{x_c^k} - x_c^k)} \left[G\left(\sum_{c\in C} \overline{x_c^k}\right) - G_k \right] - (1-\gamma)\left[\overline{p^k}\,\overline{x_c^k} - \frac{x_c^k}{\sum_{c\in C} x_c^k} G_k \right], \tag{7}$$

where $\overline{p^k}$ is the price of energy that users would have paid if their consumptions were their desired ones (no energy sheds). Parameter γ quantifies the level of incentives that CRTP provides, as described next. In case $\gamma = 0$, the CRTP($\gamma = 0$) scheme is identical to the RTP scheme,

which sees communities as "virtual" users. Our performance results will show that in this case, the pricing scheme suffers from behavioral efficiency, as it charges communities only according to the actual consumption without factorizing at all their behavioral changes, that is,

$$B_c^k(\gamma = 0) = \frac{x_c^k}{\sum_{c\in C} x_c^k} G_k \tag{8}$$

In case $\gamma = 1$, the CRTP($\gamma = 1$) pricing scheme becomes behaviorally efficient by distributing all the financial benefits $G\left(\sum_{c\in C} \overline{x_i^k}\right) - G\left(\sum_{c\in C} x_c^k\right)$ derived from the energy sheds to all the communities in a way proportional with the sheds $\overline{x_c^k} - x_c^k$ each of them performed, and thus equal to the proportional financial benefits they offered to the system.

$$B_c^k(\gamma = 1) = \overline{p^k}\overline{x_c^k} - \frac{(\overline{x_c^k} - x_c^k)}{\sum_{c\in C} (\overline{x_c^k} - x_c^k)}\left[G\left(\sum_{c\in C} \overline{x_i^k}\right) - G\left(\sum_{c\in C} x_c^k\right)\right]. \tag{9}$$

When $0 < \gamma < 1$, the CRTP(γ) model follows a hybrid strategy between the two aforementioned cases. Finally, in case where $\gamma > 1$, CRTP constitutes a more aggressive policy, in terms of behavioral efficiency, by even penalizing communities that are not performing energy sheds, thus further incentivizing communities to participate in demand response actions. In the evaluation of the proposed framework (Section 3) we look into the performance of CRTP for various values of γ and elaborate on the capabilities offered by the appropriate choice of this parameter. The first step of CRTP operation is the calculation of the community bills B_c^k for all $c \in C$ and the calculation of the $x_c^{k\prime}$s. To do so, an iterative process between the ESP and each community in C takes place. In each step m of this process, the ESP takes the new energy consumption of community c at time k, denoted as $x(m)_c^k$ with $x(0)_c^k = \overline{x_c^k}$, and calculates the new bills for all communities in C according to Eq. (7). Then, each community updates its consumption $x(m+1)_c^k$ aiming to maximize its welfare. The Community Welfare (CW) of community c at time interval k is defined as

$$CW_c^k = \sum_{i\in C} u_i^k(x(m)_i^k, \omega_i^k) - B_c^k. \tag{10}$$

In Eq. (10), each $x(m)_i^k$ (which is the energy consumption of user i at time k in the mth iteration of CRTP) is $\delta_c(m)\overline{x_i^k}$ where $\delta_c(m)\in[0,1]$ is equal for all the participating users in a community c. As it is analyzed in the next section, in order to preserve the fairness properties that this architectural decision introduces, the formation of communities takes into account the flexibility parameters of the users, so as to place in each community users with similar flexibility levels. After a number of iterations over the two aforementioned steps, CRTP converges and its outputs are the bills B_c^k and actual consumptions $x_c^k$for all $c \in C$. In order to achieve this in each steps m, it adjusts x_c^k by solving Eq. (11) to compute $\delta_c(m)$ value as follows:

$$\delta_c(m) = \arg\max_c\{CW_c^k\} \tag{11}$$

After the calculation of the final community bills, the next process is the calculation of the bill of each participating user. In our model, users participate in the bill of their community in a way proportional to their actual consumption x_i^k.Thus the bill B_i^k for user i in time interval k is given by:

$$B_i^k = \frac{x_i^k}{\sum_{i\in C} x_i^k} B_c^k \tag{12}$$

More advanced policies that distribute the bill of each community to its members has been already described in our previous work [5] and are outside the scope of this work. CRTP is transparent to these policies and can be combined with any of them.

3.5. Criteria that determine the formation of the virtual energy communities

Based on the philosophy of the CRTP scheme, which is to incentivize communities, exploit social interactions, but also be fair, we derive two criteria as the most appropriate ones to play a role towards the creation of the VECs. The first criterion is the flexibility similarity levels of the participating users, which is modeled here through flexibility parameter ω_i^k. In view of Eq. (7), users with similar flexibilities perform similar energy sheds. Thus, ECFA groups users with similar flexibilities towards the development of a fair pricing model, especially given that the distribution of profits among the members of the community (Eq. (12)) is based on their consumption and not on their individual contribution. Otherwise, if we placed in the same VEC users with very disparate flexibilities, non-flexible users would unfairly benefit from the actions of flexible users in the same VEC. In addition, the optimization of the community welfare (Eq. (10)) is much more behavioral efficient in this case.

The second criterion of the communities' formation is the social correlation of the participating users. The VECs' formation according to social correlation among its members has been found to result into effective behavioral changes. In more detail in [11], the results on a social network peer pressure show that the influence is not only related to its connectivity, but it is also strongly affected by node-to-node social weights. Energy savings reported in [11] start from 5.64% and reach up to 25%. Related research findings in [29,30], found the effect of group-level feedback and peer education on energy reductions to be in the range from 4% to 7%. Thus, in the energy efficiency sector, there are already some initial attempts to exploit social networks (modelling the capabilities of peer pressure) in order to achieve a behavioral change in the energy consumption. On the other hand, there is no pricing model yet able to automate and exploit these phenomena. In addition, there are no experimental studies and results from other areas/sectors in order to quantify through simulations the expected improvements.

3.6. Energy Community Formation Algorithm (ECFA)

The implementation of ECFA is done through the use of spectral clustering [8,22], which is one of the most widely used algorithms for clustering, thanks to its ease of implementation, simplicity, efficiency and empirical success. According to ECFA, the set N of consumers is clustered into a set of communities $C = \{c_1, c_2, ..., c_{|C|}\}$. ECFA takes into account the flexibility of each consumer and his/her connections in online social networks. In particular, the distance metric between two consumers i and j used for clustering is:

$$d(i,j) = w_1\cdot(1 - ((\omega_i - \omega_j)/\max(\omega_i, \omega_j))) + (1 - w_1)\cdot f(i,j) \tag{13}$$

Parameter $w_1\in[0,1]$ can be used to obtain a trade-off between the similarity in the flexibilities ω_i and ω_j of users i and j, and the strength $f(i,j)$of their social connections, as described later. User flexibility could be declared by the users and monitored/validated in practice, or be measured through historical data (e.g. user's recent behavior). Parameter $f(i,j) \in [0,1]$ represents the level of social connection between i and j and is defined as

$$f(i,j) = 0.5\cdot Fr(i,j) + 0.5\cdot Cf(i,j)/Tf(i,j) \tag{14}$$

In Eq. (14), $Fr(i,j)$ is 1 if i is socially connected with j in OSNs, $Cf(i,j)$ is the number of common social connections between i and j in OSNs and $Tf(i,j)$ is the sum of the social connections of i and j in OSNs. The definition of Eq. (14) is motivated from observations from field trials [11,12,23,24]. Other definitions of $f(i,j)$ could have been used in our proposed framework, and the specific definition is used only in our performance results.

The objective of ECFA is to group consumers into VECs, so that consumers in the same VEC are similar to each other, with the index of

similarity expressed through the distance metric of Eq. (13). This distance metric among consumers forms the input values to the similarity matrix, and the well- spectral clustering technique [8] is then used to group consumers in a predefined number of clusters. The optimal value of w_1 in Eq. (13) according to which ECFA takes place is dataset dependent and it also depends on the impact that social connections have on the modification of the flexibility levels of the consumer. Finally is quantified the effect of peer pressure (pp) that a community $c \in C$ has on the flexibility (ω_i according to the definition of Section 3.1) of a peer $i \in c$. Based on relevant field trials [11,12,23,24], we assume that the peer pressure impact is quantified as a reduction of the flexibility parameter (increase in flexibility) from the a priori value ω_i to an a posteriori (after the peer pressure) value of ω_pp_i given by:

$$\omega\_pp_i = \omega_i{}^{*}argmax_{j\in C}[1 - max_{pp}{\cdot}f(i,j)] \tag{15}$$

Thus, ω_pp_i is the flexibility parameter of consumer i after the peer pressure caused by community formed by ECFA. Here, $max\_pp \in [0.1]$ is the maximum percentage in which peer pressure effect is able to modify flexibility of consumers.

4. Performance evaluation results

In this section, we evaluate our proposed CRTP-ECFA scheme, which will from now on be referred to simply as CRTP for brevity, by using the RTP scheme as a benchmark for comparisons. We consider a system consisting of $N = 64$ energy consumers and simulate a period of one day. Unless otherwise stated, we set $c = 0.02$ in the energy cost generation function of Eq. (3), and use ECFA to form $|C| = 16$ VECs. To evaluate the proposed system, we use the following Key Performance Indicators (KPIs), also widely accepted in the literature [15,16,21]:

1) Energy Cost G, as defined in Eq. (3), which is the cost of ESP to acquire the electricity needed to fulfill the requirements of its customers. This is an index of how energy-efficient a pricing scheme is in terms of incentivizing its customers to adopt energy-efficient habits.
2) Aggregate Users' Welfare AUW is a KPI that summarizes UW, given by Eq. (5), and expresses the competitiveness of an ESP that adopts a billing strategy in an open retail electricity market.
3) Behavioral Reciprocity BR_i of user i is the degree of correlation between the behavioral change of i and the reward that i gets for it:

$$BR_i = \frac{D_i^A}{D_i^R}, \forall\, i \in N \tag{16}$$

where D_i^A(Eq. (17)) represents the discount achieved, i.e. the system cost reduction, for user i and D_i^R (Eq. (18)), represents the discount received by i, i.e. the difference between user i's bill with the original system's state ($x_i^t = \widetilde{x_i^k}\ \forall\, i \in N$) and the actual user i bill (after applying RTP or CRTP). This is expressed mathematically as,

$$D_i^A = \left(\widetilde{x_i^k} - x_i^k\right)\cdot\frac{\left[G\left(\sum_{i=1}^{N}\ \widetilde{x_i^k}\right) - G\left(\sum_{i=1}^{N}\ x_i^k\right)\right]}{\sum_{i=1}^{N}\ \widetilde{x_i^k} - \sum_{i=1}^{N}\ x_i^k} \tag{17}$$

$$D_i^R = \widetilde{x_i^k}\cdot\left[\frac{G\left(\sum_{i=1}^{N}\ \widetilde{x_i^k}\right)}{\sum_{i=1}^{N}\ \widetilde{x_i^k}}\right] - x_i^k{\cdot}p_i^k \tag{18}$$

Values of BR_i close to 1 indicate a better trade-off between AUW and G, and thus a fairer pricing mechanism. In the rest of this section, we present five studies. The first observes the performance of CRTP under various values of γ and energy generation cost models (Eq. (3)) in order to justify the importance of the design of a pricing scheme to motivate behavioral changes to the end users. The second studies how CRTP reacts under various levels of user's flexibility in order to prove that the proposed system is not data-dependent. The third evaluates the performance of CRTP under different assumptions on the number $|C|$ of VECs and different peer pressure levels (Eq. (15)) in order to demonstrate their impact in promoting behavioral change towards energy efficiency. The fourth compares CRTP with ECFA to CRTP without ECFA in order to justify the necessity of the interaction of these two components. Finally, the fifth compares an ECFA that takes into account multiple criteria, namely the user's flexibility and the user's social connections, with two ECFAs that take into account only one of them in order to justify our decision to design VECs with multiple criteria.

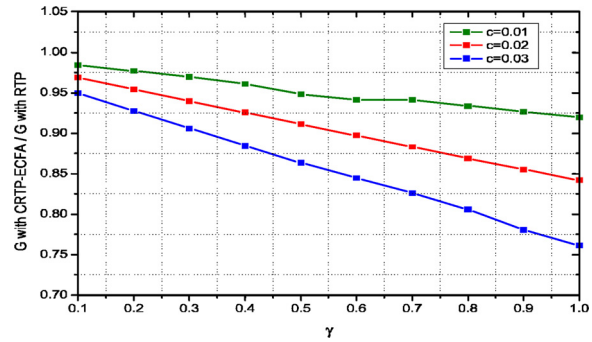

Fig. 2. Ratio between G under CRTP-ECFA and G under RTP, as a function of γ for various energy generation cost parameters c.

4.1. Study for varying generation cost of energy in the wholesale electricity market

Fig. 2 depicts the ratio between the consumed energy cost G under CRTP-ECFA and also under RTP as a function of γ, for three different choices of the energy generation cost parameter, $c = 0.01$, 0.02 and 0.03. The total percentage of energy cost reduction for $\gamma = 1$ varies from 8% for low generation cost of energy ($c = 0.01$) to 24% for high generation cost of energy ($c = 0.03$) for a given number $|C| = 16$ of VECs. It is apparent that in all scenarios, γ parameter highly affects the system's energy cost G.

Fig. 3 depicts the ratio between AUW under CRTP-ECFA and AUW under RTP again as a function of γ, under the same scenarios used in Fig. 2 (c takes values 0.01, 0.02 and 0.03). As we observe, the AUW under CRTP-ECFA is also higher than AUW in RTP and this increase ranges from 2% to 5%. Low values of γ favor inflexible users while high values favor flexible ones. In the zone of γ around 0.6 to 0.8, there is an attractive trade-off between the welfare, given by Eq. (5), of both flexible and inflexible users. On the other hand, the value of γ that maximizes AUW depends on parameter c, the ECCs of the consumers, and their flexibility levels. It is infeasible to calculate theoretically the value of γ at which the ratio AUW under CRTP-ECFA/AUW under RTP

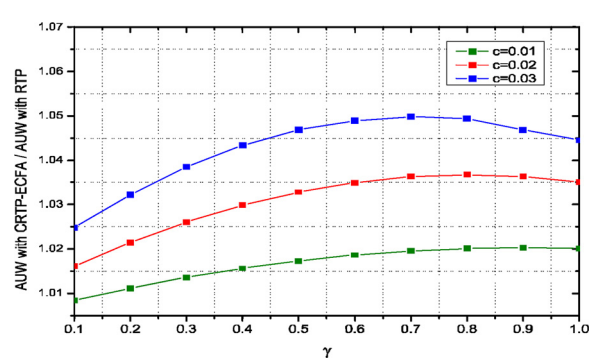

Fig. 3. Ratio between AUW with CRTP-ECFA and AUW with RTP, as a function of γ.

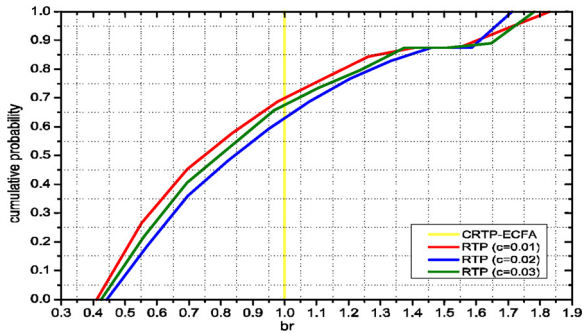

Fig. 4. CDF of BR in RTP and CRTP-ECFA for different energy generation costs.

is maximized, and ESPs have to adjust γ empirically through software tools for business analytics like these that SOCIALENERGY project [6] proposes.

In Fig. 4, the Cumulative Distribution Function (CDF) of the *BR* under RTP and under CRTP-ECFA is presented for various choices of the energy generation cost parameter *c*. As observed, CRTP-ECFA is capable to fairly distribute the financial benefits that are caused by the behavioral changes taking place to the VECs that perform these behavioral changes. On the contrary, RTP is a volume-aware pricing, which does not incentivize behavioral changes because it is not fair.

As Fig. 4 depicts, there is high variance of *BR* among the participating users. Some of the users (i.e. highly flexible users) are rewarded less than 50% of their contribution to the system's energy savings, while others (i.e. low flexibility users) are rewarded more than what their contribution is worth. In contrast, the yellow line obtained for CRTP-ECFA shows that all users get reimbursed exactly based on each one's contribution to the system's energy cost reduction.

4.2. Study for varying levels of users' flexibility

Fig. 5 presents the ratio between the consumed energy cost *G* with CRTP-ECFA and with RTP as a function of γ for various average level of user flexibility [parameter *ω* in Eq. (2)]. Three different scenarios (noted as "LOW", "MEDIUM", "HIGH") were executed based on the value of the users' flexibility parameters *ω*. In these scenarios, the elasticity parameter *ω* of each user is chosen randomly in the interval [9,17] for LOW flexible users, in the interval [4,10] for MEDIUM flexible, and in the interval [0.5,7] for HIGH flexible users. We note here that this set of scenarios is a superset of the scenarios analyzed in [14,21,29], where similar studies were reported. As we observe, significant cost reductions are achieved starting with ~11% for inflexible users and reaching up to 35% for flexible users, without sacrificing at all the user's welfare (competitive services).

Fig. 6 depicts the ratio between aggregated users' welfare *AUW* with CRTP-ECFA and *AUW* with RTP, again as a function of γ for the same three LOW/MEDIUM/HIGH flexibility scenarios. CRTP-ECFA achieves

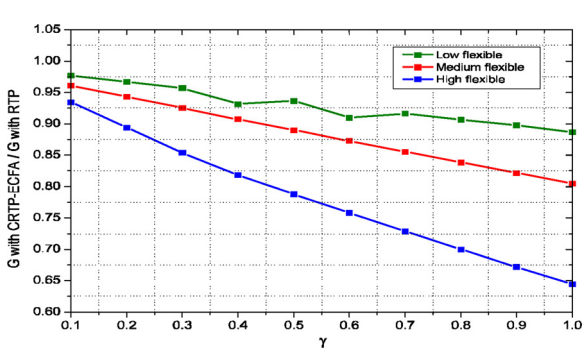

Fig. 5. Ratio between energy generation cost *G* with CRTP-ECFA and *G* with RTP as a function of γ, for different user flexibility levels.

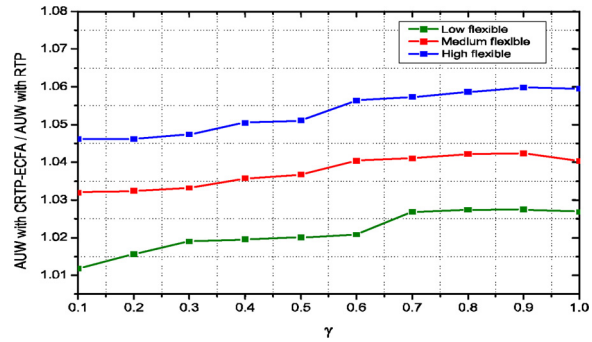

Fig. 6. Ratio between AUW with CRTP-ECFA and AUW with RTP as a function of γ, for multiple user flexibility levels.

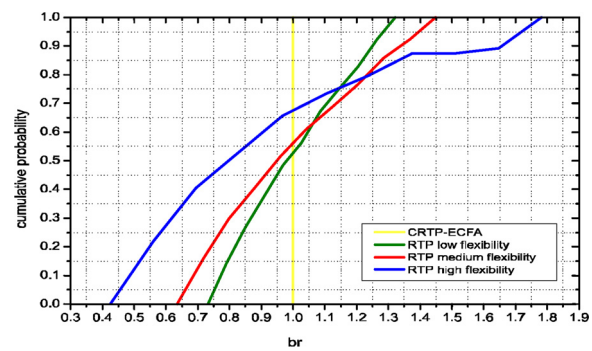

Fig. 7. CDF of BR in RTP and CRTP-ECFA for various user flexibility levels.

better performance in all scenarios, which range from 3% (LOW) to 6% (HIGH). In the latter case, the increase of AUW with CRTP-ECFA is higher than that with RTP as higher flexibility allows CRTP-ECFA more options to use this trade-off more efficiently.

Fig. 7 depicts the Cumulative Distribution Function (CDF) of *BR* with RTP and with CRTP-ECFA, for different levels of the users' flexibility. We observe that CRTP-ECFA is able to fairly distribute the financial benefits among all the users. Also, the level of unfairness in RTP increases when users have higher flexibility levels (cf. blue line). In these cases, RTP fails to reward flexible users and thus we observe even higher variance in *BR*.

4.3. Study for varying average size of VECs and peer pressure factor

Fig. 8 depicts the ratio between the generation cost *G* with CRTP-ECFA and *G* with RTP as a function of maximum peer pressure effect [parameter *max_pp* in Eq. (15)] for multiple numbers of VECs (or else multiple average VEC size). As we observe, as the *max_pp* increases, larger number of VECs achieve greater cost reduction. Fewer number of consumers in each VEC leads to well structured groups as the flexibility

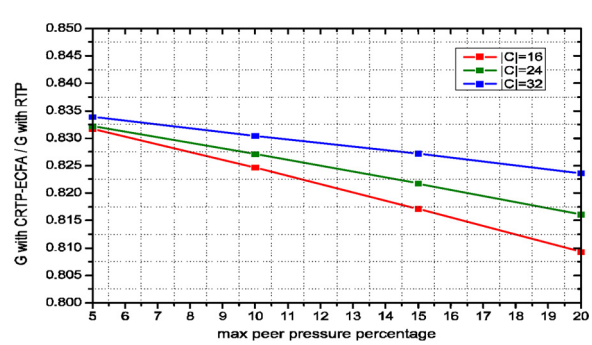

Fig. 8. Ratio between energy generation cost *G* with CRTP-ECFA and *G* with RTP as a function of maximum peer pressure effect for multiple VEC formations.

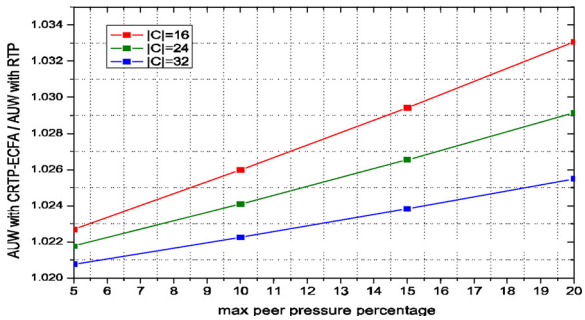

Fig. 9. Ratio between AUW under CRTP-ECFA and AUW under RTP, as a function of maximum peer pressure effect for different sizes $|C|$ of the VEC formations.

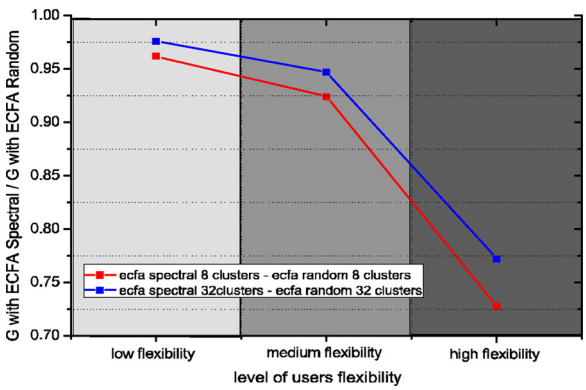

Fig. 10. Ratio between between energy generation cost G under CRTP with ECFA and G under CRTP with random VECs as a function of user's flexibility.

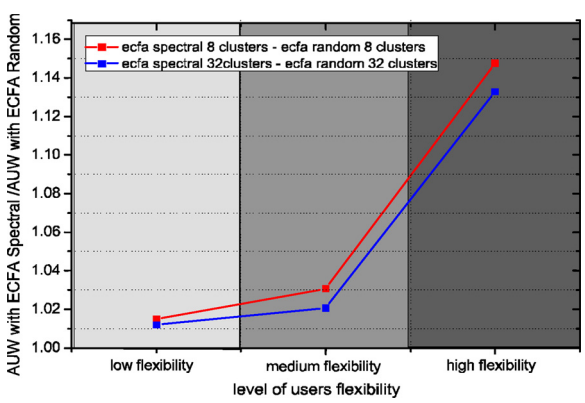

Fig. 11. Ratio between AUW (CRTP with ECFA) and AUW (CRTP with random VECs) as a function of users' flexibility.

and social similarity becomes optimal. As a result, greater amounts of consumption reduction are achieved.

Additionally, Fig. 9 presents the ratio between *AUW* under CRTP-ECFA and *AUW* under RTP as a function of *max_pp* for multiple numbers of VECs. In this case, three case scenarios were validated: 64 users were divided into 16 VECs for the first senario, into 24 VECs for the second scenario, and finally into 32 VECs. As *max_pp* increases, the total cost reduction ranges from 15% to 20% depending on the number of VECs. In addition, as expected, as *max_pp* increases, AUW also increases (by around 2%), which means that the exploitation of the peer pressure effect improves both KPIs.

4.4. Outperformance of ECFA and spectral clustering technique

In Fig. 10, we present the ratio between the energy cost G with CRTP when the VECs are generated using the ECFA scheme, and the energy cost G with CRTP when the VECs are generated randomly; this ratio is depicted as a function of the flexibility level of the participating users. Results indicate a significant reduction in G, between 5% for users with low flexibility and up to 35% for users with high flexibility, through the use of ECFA in CRTP. This improvement was expected as the ECFA intelligently groups the users in the most appropriate VECs, as opposed to the case where the VECs are randomly created.

Finally, In Fig. 11, we depict the ratio between the *AUW* under CRTP in case that VECs are generated through the use of ECFA and the *AUW* under CRTP in case that VECs are generated randomly. This ratio is again shown as a function of the flexibility level of the participating users. According to Fig. 11, there is a considerable increase in *AUW* that starts from 3% in case of low flexibility and $|C| = 8$ and reaches 15% in case of high flexibility and $|C| = 16$. Figs. 10 and 11 illustrate the importance of combining CRTP with an intelligent Energy Community creation algorithm, like ECFA, towards obtaining an efficient pricing scheme.

4.5. Study of the multi-parametric objective function for VECs'creation

Table 2 presents the ratio between G under CRTP-ECFA and G under RTP, while Table 3 presents the ratio between *AUW* under CRTP-ECFA and *AUW* under RTP, for various values of the weighting parameter w_1 used in Eq. (13). In column 2 (or 4) of these tables, scenarios in which ECFA takes into account only the flexibility levels (or only the social connections, respectively) for the formation of VECs are presented. On the other hand, column 3 presents a multi-criteria scenario, where both flexibility in energy consumption and social connections were equally taken into account through the use of ECFA. As we observe from Table 2 and Table 3, for each scenario (and regardless of the flexibility level of the consumers), the use of multiple criteria provides the maximum behavioral change (minimum cost), while it increases *AUW* at the same time.

5. Conclusions and future work

We proposed a novel Community aware − Real Time Pricing (CRTP) scheme that reduces system's energy cost without sacrificing at all the aggregated users' welfare. CRTP allocates the demand response gains fairly among the users and promotes behavioral change towards energy efficiency. The average energy cost savings obtained are about 10–20%, while they even reach 30% under certain scenarios, where users are very flexible. The proposed Energy Community Formation Algorithm (ECFA) can be used by an ESP's business to automatically form efficient VECs that achieve high behavioral change. The proposed schemes have been implemented in the SOCIALENERGY S/W platform [6]. VECs can be used as input to various business analytics functionalities such as user profiling, reporting and recommendation

Table 2
The ratio between G in CRTP and G in RTP under various values of w_1 in ECFA (trade-off between flexibility and social factor).

G(CRTP)/G(RTP)	Flexibility only ($w_1 = 0$)	Social & flexibility factors ($w_1 = 0.5$)	Social factor only ($w_1 = 1$)
Low flex users	0,88	0,86	0,91
Medium flex users	0,78	0,76	0,81
High flex users	0,69	0,65	0,76

Table 3
The ratio between AUW in CRTP and AUW in RTP under various values of $w1$ (trade-off between flexibility and social factor).

AUW(CRTP)/AUW(RTP)	Flexibility factor only (w_1 = 0)	Social & flexibility (w_1 = 0.5)	Social factor only (w_1 = 1)
Low flex users	1,00	1,03	1,01
Medium flex users	1,03	1,06	1,03
High flex users	1,02	1,04	0,94

mechanisms towards achieving higher and sustainable user engagement. In our future work, we plan to investigate a more dynamic and advanced ECFA operation for VECs' adaptation and extend CRTP to efficiently allocate the monetary benefits to the members of a single VEC via a novel policy of mixed VEC and personalized RTP model.

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References

[1] Ye Yan, et al., A survey on smart grid communication infrastructures: motivations, requirements and challenges, IEEE Commun. Surv. Tutorials 15 (2013) 5–20.
[2] J. Vardakas, N. Zorba, C. Verikoukis, A survey on demand response programs in smart grids: pricing methods and optimization algorithms, IEEE Commun. Surv. Tutorials 17 (2015) 152–178.
[3] B.P. Koirala, et al., Energetic communities for community energy: a review of key issues and trends shaping integrated community energy systems, Renewable Sustainable Energy Rev. 56 (April) (2016) 722–744.
[4] Flexible Power Alliance Network Power Matcher Suite 2015. Available online: http://flexiblepower.github.io/why/powermatcher/. (Accessed 10 September 2017).
[5] N. Doulamis, A. Doulamis, E. Varvarigos, Virtual associations of prosumers for smart energy networks under a renewable split market, IEEE Trans. Smart Grid (2017).
[6] P. Makris, N. Efthymiopoulos, V. Nikolopoulos, A. Pomazanskyi, B. Irmscher, K. Stefanov, K. Pancheva, E. Varvarigos, Digitization era for progressive electric utilities: a novel business model through an inter-disciplinary S/W platform and open research challenges, IEEE Access 6 (2018) 22452–22463.
[7] A. Mani, I. Rahwan, A. Pentland, Inducing peer pressure to promote cooperation, Nat. Sci. Rep. 3 (2013) Article number: 1735.
[8] D.J. Vergados, I. Mamounakis, P. Makris, E. Varvarigos, Prosumer Clustering into virtual microgrids for cost reduction in renewable energy trading markets, Sustain. Energy Grids Net. (SEGAN) 7 (2016) 90–103 Elsevier.
[9] F. Grossberg, et al., Gamified Energy Efficiency Programs, ACEEE Report Number B1501, February 2015.
[10] Yu-kai Chou, Actionable Gamification: Beyond Points, Badges, and Leaderboards, Create Space Independent Publishing Platform, 2015. Available: http://www.amazon.com/Actionable-Gamification-Beyond-Points-Leaderboards-ebook/dp/B00WAOGY4U.
[11] F. Du, J. Zhang, H. Li, J. Yan, S. Galloway, K.L. Lo, Modelling the impact of social network on energy savings, Appl Energy 178 (2016) 56–65 Elsevier.
[12] R. Jain, R. Gulbinas, J. Taylor, P. Culligan, Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback, Energy Build. 66 (2013) 119–127 Elsevier.
[13] N. Li, L. Chen, S.H. Low, Optimal demand response based on utility maximization in power networks, IEEE Power and Energy Society General Meeting, Detroit, USA, 2011, pp. 1–8.
[14] P. Samadi, H. Mohsenian-Rad, R. Schober, V.W.S. Wong, Advanced demand side management for the future smart grid using mechanism design, IEEE Trans. Smart Grid 3 (2012) 1170–1180.
[15] Baharlouei, et al., Achieving Optimality and fairness in autonomous demand response: benchmarks and billing mechanisms, IEEE Trans. Smart Grid 4 (2013) 968–975.
[16] Baharlouei, et al., Efficiency-fairness trade-off in privacy-preserving autonomous demand side management, IEEE Trans. Smart Grid 5 (2014) 799–808.
[17] L. Gkatzikis, I. Koutsopoulos, T. Salonidis, The role of aggregators in smart grid demand response markets, IEEE J. Sel. Areas Commun. 31 (2013) 1247–1257.
[18] H.M. Soliman, A. Leon-Garcia, Game-theoretic demand-side management with storage devices for the future smart grid, IEEE Trans. Smart Grid 5 (2014) 1475–1485.
[19] Z. Wang, R. Paranjape, Optimal residential demand response for multiple heterogeneous homes with real-time price prediction in a multiagent framework, IEEE Trans. Smart Grid 99 (2015) 1–12.
[20] N. Yaagoubi, H.T. Mouftah, User-aware game theoretic approach for demand management, IEEE Trans. Smart Grid 6 (2) (2015) 716–725.
[21] P. Samadi, et al., Optimal real-time pricing algorithm based on utiltiy maximization for smart grid, Proc. 1st IEEE Intl Conference on Smart Grid Communications (SmartGridComm), Gaithersburg, USA, 2010.
[22] A.Y. Ng, M.I. Jordan, Y. Weiss, On spectral clustering: analysis and an algorithm, in: T.G. Dietterich, S. Becker, Z. Ghahramani (Eds.), In Proceedings of the 14th Intl Conference on Neural Information Processing Systems: Natural and Synthetic (NIPS'01), MIT Press, Cambridge, MA, USA, 2001, pp. 849–856.
[23] R. Castri, V. De Luca, E. Lobsiger-kägi, C. Moser, V. Carabias, Favouring behavioural change of households' energy consumption through social media and cooperative play. 2014.
[24] E. Azar, C.C. Menassa, Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings, Energy Build 97 (2015) 205–218.
[25] F.-L. Meng, X.-J. Zeng, A Stackelberg game-theoretic approach to optimal real-time pricing for the smart grid, Soft Comput 17 (2013) 2365–2380 Springer.
[26] R. Deng, et al., Residential energy consumption scheduling: a coupled-constraint game approach, IEEE Trans. Smart Grid 5 (2014) 1340–1350.
[27] R. Deng, Z. Yang, J. Chen, M.Y. Chow, Load scheduling with price uncertainty and temporally-coupled constraints in smart grids, IEEE Trans. Power Systems 29 (2014) 2823–2834.
[28] L. Jiang, S. Low, Multi-period optimal energy procurement and demand response in smart grid with uncertain supply, 50th IEEE Conference on Decision and Control and European Control Conference, Orlando, FL, 2011, pp. 4348–4353.
[29] J. Ma, J. Deng, L. Song, Z. Han, Incentive mechanism for demand side management in smart grid using auction, IEEE Trans. Smart Grid 53 (2014) 1379–1388.
[30] A.R. Carrico, M. Riemer, Motivating energy conservation in the workplace: an evaluation of the use of group-level feedback and peer education, J. Environ. Psychol. 31 (2011) 1–13.
[31] Wei Tang, Zhengdong Lu, Inderjit S. Dhillon, Clustering with multiple graphs, IEEE International Conference on Data Mining (ICDM) (2009) 1016–1021.
[32] Rob van Gerwen, Hans de Heer, Flexibility value chain, Universal Smart Energy Network, 2015. (USEF position paper).