A Novel Pricing Scheme for Virtual Communities Towards Energy Efficiency

Ioannis Mamounakis[a,b], Nikolaos Efthymiopoulos[b], Georgios Tsaousoglou[b], Dimitrios J. Vergados[a,b], Prodromos Makris[b], Emmanouel Varvarigos[b,c]

[a] Computer Technology Institute & Press "Diophantus", Rio Patras, Greece

[b] Institute of Communication and Computer Systems, National Technical University of Athens (NTUA), Greece

[c] Dept. of Electrical and Computer Systems Engineering, Monash University, Australia

Email: {{mamunak, prodromosmakris, vmanos}@central.ntua.gr, {nikoseft, geotsaousoglou, djvergad}@mail.ntua.gr}

***Abstract*— A major challenge in an open and competitive electricity market that exploits renewable energy sources is the alignment between the variable rate energy production and the ad hoc energy consumption of the end users. In this context, there is a need for modern pricing schemes that will be able to effectively incentivize willing users towards modifying their energy consumption pattern based on current conditions. Existing pricing schemes treat all users the same, thus mitigating the behavioral change dynamics. To address this deficiency, we propose a Community Real Time Pricing (C-RTP) model, where users form communities and are charged according to the energy behavior of their entire community. The proposed C-RTP system is compared against the most widely accepted model in the literature, the RTP pricing model, and is shown to achieve lower energy cost (10%-15%) without sacrificing the end users' welfare or the profits of the energy service provider.**

Keywords—smart grid; clustering; virtual energy communities; community energy pricing;energy efficiency

I. Introduction

The recent adoption of smart grid technologies and the liberalization of electricity markets have already brought considerable efficiency benefits in the electricity system's operation, mainly by reducing the cost of energy and facilitating the further penetration of renewable energy sources (RES). Moreover, innovative differentiated energy services are being offered to end consumers, who can now get better price tariffs by providing their flexibility to the grid. Finally, new business opportunities arise for new as well as existing market stakeholders.

A major challenge in this new environment is the continuous alignment of the variable rate energy production with the ad hoc energy consumption of the end users [1]. At the supply side, the main challenges relate to the unpredictable and volatile nature of RES, the need to maximize RES penetration without affecting the normal grid's operation, and the reduction of energy production cost. At the demand side, the main challenges relate to the engagement of consumers in innovative demand response programs and their behavioral change towards flattening (or, more generally, shaping in the desired way) the aggregated energy consumption curve [2]. Towards these goals, the research community focuses on the development of architectures that automatically align production with consumption by enabling a dynamic and sophisticated interaction between the pricing of energy and the way (i.e. scheduling) end users consume it [3], [4]. The design of this type of architectures is based on innovative concepts found in the literature, like the decentralized management of the energy system [5], the local electricity markets' operation [6], the integrated community energy systems (ICES) [3], the virtual microgrid/prosumer associations [7], [8], the prosumer community groups [9], and cooperative demand response [10].

Closely following these research trends, in the commercial sector, progressive electric utilities (or else Energy Service Providers - ESPs) are trying to engage their customers in innovative energy programs (EPs) via the use of digital S/W platforms that offer community-level and personalized energy services to the users [11]. As a result, the need for innovative pricing models that go beyond the traditional real-time pricing (RTP) model has emerged.

An efficient pricing model has to fulfill several requirements by achieving an attractive trade-off between i) the end user's satisfaction, ii) the ability of the model to affect the behavior of the participating users towards a more efficient energy production/transmission/distribution/retail system, and iii) the financial profitability of the ESP that offers energy services accordingly. The first requirement (metric) is denoted as "user's welfare" (UW) and is formulated according to a utility function that expresses the degree to which an end user values a specific consumption pattern and the cost of energy that s/he consumes. In the context of comparing two pricing models, UW expresses which model leads to more competitive services in the market. The second requirement, also called "behavioral efficiency", expresses the ability of a pricing scheme to achieve the objectives that motivate its use (e.g., energy sheds and shifts). Intuitively, behavioral efficiency of a pricing scheme indicates how friendly it is to a TSO/DSO (in addressing issues relevant to energy network stability, efficiency and costs). Usually, it is also linked with minimizing the system's energy cost, which is the main metric used in this paper. The third requirement is also referred to as "profit dynamics" and represents the profits of the ESP. In other words, it expresses the financial growth potential of an ESP using the specific pricing model and, implicitly, the sustainability of its business.

In the context of the EU-funded H2020 SOCIALENERGY project [12], we try to facilitate the easy, rich and deep

978-1-5386-3669-5/18/$31.00 ©2018 IEEE

communication between stakeholders in energy efficiency and end users in a way that will allow them to: i) discover each other, ii) educate themselves so as to understand the difficulties and challenges each one faces, and iii) finally, interact and trade with each other via the use of community EPs. Under this perspective, in this paper, we focus on the development of a pricing scheme that organizes end users in Virtual Energy Communities (VECs) and gives end users the opportunity to have direct financial benefits based on the actions their VEC takes and their resulting aggregated energy consumption. VECs can be viewed as community (social) aggregators of flexibility. Our aim is, through a Community – Real Time Pricing (C-RTP) model, to avoid the well-known problem of the tragedy of the commons [13], where users do not change their behavior due to the negligible impact that this change would have on their lives. In contrast, in our proposed framework, every demand response (DR) action taken by an individual user affects the whole community and this constitutes a socially-derived incentive for her/his behavioral change. In addition, the proposed C-RTP model is able to treat VECs in a differentiated way, according to their measured flexibility towards achieving a well-targeted and feasible behavioral change effect at the minimum cost. Finally, we expect that in real life the social influence inside the communities will play a critical role on the behavioral dynamics of the participating users, which will further increase the performance of the proposed system beyond its aggregation advantages.

In addition to meeting the previously described objective requirements, a pricing scheme has to be designed according and be tuned to the environment in which it will operate. Each scheme proposed in the literature aims to a specific environment. In this work, we assume automated houses and/or buildings where electric appliances are controlled through automated algorithms. The energy consumption of a user in the absence of any external stimulus (i.e., lack of additional motive or price penalty or DR action) is a varying function of time, and will be referred to as his/her voluntary or spontaneous consumption. Designing a pricing scheme for the case of a priori *known* voluntary energy consumption is different than designing one for the case of a priori *unknown* voluntary energy consumption. In addition, a pricing scheme that incentivizes energy cuts is different from one that incentivizes energy shifts. In this work, we demonstrate the concept of the Community Real Time Pricing for energy cuts and a priori known voluntary energy consumptions. Its demonstration in scenarios that include energy shifts and unknown voluntary energy consumption is left as future work.

Thus, in a nutshell, the main contributions of this paper are:

- A Community– Real Time Pricing (C-RTP) scheme that rewards flexible communities and achieves an attractive trade-off among the aforementioned requirements.
- An Energy Community Formation Algorithm (ECFA) that accounts for the flexibility of participating users. ECFA feeds our pricing model with VECs (clusters of users) that are able to maximize C-RTP's performance.
- A comparison of the proposed C-RTP with the recently developed RTP models, which proves experimentally the improvements C-RTP can bring about with respect to the aforementioned pricing model requirements.

The rest of this work is structured as follows: Section II analyzes the proposed community formation algorithm and the C-RTP model. Our framework is evaluated and compared with the recently developed RTP schemes, while research insights are given about the use of the results in the real business of progressive and digitalized electric utilities. Finally, Section III provides our conclusions and directions for future work.

II. Problem Formulation and the Proposed Energy Community pricing scheme

The presentation of the proposed framework is organized in four subsections, dealing with: i) background knowledge on RTP, which will also serve as the benchmark scheme for our comparisons, ii) description of Community Real Time Pricing (C-RTP), iii) presentation of Energy Community Formation Algorithm (ECFA) and iv) our evaluation methodology.

Without harm of generality, the end users (energy consumers) that participate in the system form a set $N = \{1, 2, \dots, n\}$. Each user i possesses a smart meter, which is a device that is able to monitor its Energy Consumption Curve (ECC). We consider a finite time horizon that is fragmented into time intervals, forming a set $H = \{1, 2, \dots, h\}$. All time intervals in H are of equal (but arbitrary) length. According to ECFA, each user i belongs to exactly one community c and the set of the communities form set C. Each user i is characterized by his/her voluntary energy consumption $\overline{x_i^k}$ during time interval k, which is assumed to be known a priori. Note that the voluntary energy consumptions are different for different users and timeslots. The effect of the DR program a user participates in (or of the C-RTP pricing scheme, in our case) is to change its voluntary (spontaneous) consumption into its actual consumption denoted by x_i^k. Eq. (1) gives the voluntary and the actual consumption of community c during time interval k:

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

A. Real Time Pricing (RTP)

Existing RTP models [17], [21] calculate the prices during each time slot k through the following iterative process. Initially, users set their voluntary consumptions $\overline{x_i^k}$, for all $i \in N$ and $k \in H$. Next, the ESP calculates the price per energy unit according to:

$$p^k = (1+\pi)\frac{G_k(\sum_{i=1}^N x_i^k)}{\sum_{i=1}^N x_i^k} \tag{2}$$

where $G_k(\sum_{i=1}^N x_i^k)$ is the cost of generating $\sum_{i=1}^N x_i^k$ units of energy at time slot k, and π is the profit percentage desired by the ESP. The energy generation cost $G_k(x)$ is usually approximated as an increasing and convex function of x. In Eq. (2), price p^k is calculated as the overall per unit generation cost (i.e., ratio of the total energy cost G_k at time k over the total energy consumption), and is increased by the profit percentage. Subsequently, in response to the price set by the ESP, each user adjusts her/his actual consumption x_i^k in order to maximize her/his welfare. The User Welfare (UW) of i at time interval k is defined as:

$$UW_i^k = u_i^k(x_i^k, \omega_i^k) - p^k x_i^k \quad (3)$$

where the utility function $u_i^k(x_i^k, \omega_i^k), k \epsilon H,$ of user $i\epsilon N$ expresses how much (in monetary units) user i values the consumption of x_i^k energy units at time k, and ω_i^k is a user and time specific flexibility parameter, to be described in Subsection II.C. In the performance analysis section, we demonstrate the performance of C-RTP for a specific form of $u_i^k(x_i^k, \omega_i^k)$ which is popular in the literature. Through the iterative execution of Equations (2) and (3) the system converges to the final prices p^k for all intervals $k\epsilon H$ and all users $i\epsilon N$, which maximize the welfare of the users.

Thus, in RTP the energy scheduling problem at timeslot k can be viewed as the pricing decisions and the interaction of pricing with the users' voluntary energy consumption and utility functions in order to obtain the actual energy consumptions that minimize energy costs G_k, while maximizing each user's welfare UW_i^k. These also determine the profit margins of the ESP/retailer in the open electricity market. Again, we remind the reader that we only consider the case of energy shedding, while the case of energy shifts is left for future work.

B. Community Real Time Pricing (C-RTP)

As discussed earlier, the problem with RTP model is that it does not incentivize changes (i.e., load sheds and shifts) in the ECC of the users. Since the energy generation cost $G_k(x)$ is an increasing and convex function, when a user decreases her/his energy consumption she/he doesn't only cause a reduction in the total cost of energy $G_k(x)$ but also reduces the average per unit generation cost $G_k(x)/x$, and thus the price of energy as depicted in Eq. (2). Thus, with RTP the benefits of a specific user's DR actions are distributed to all users in a way analogous to their actual consumption and not to their contribution (actual reduction) to the DR action. Hence, a user may gain from the behavioral change of another user, even if s/he didn't perform any change in her/his ECC.

In contrast to RTP, in our proposed Community Real Time scheme C-RTP, users are clustered into communities and are presented with a pricing model that factorizes the desired and actual consumption of the participating communities in order to enhance RTP with behavioral efficiency (reward each community for its DR actions). More specifically, we charge a community c at each time period k according to its aggregate voluntary energy consumption $\overline{x_c^k}$ and the aggregate actual energy consumption x_c^k. The aggregate bill of community c in a time interval k, denoted by B_c^k, is calculated as:

$$B_c^k = \overline{p^k x_c^k} - (1+\pi)\frac{\left(\overline{x_c^k} - x_c^k\right)}{\sum_{m\in C}\left(\overline{x_m^k} - x_m^k\right)}\left[G\left(\sum_{m=1}^{C}\overline{x_m^k}\right) - G\left(\sum_{m=1}^{C} x_m^k\right)\right] \quad (4)$$

In Eq. (4), $\overline{p^k}$ is the price of energy that users would have paid if their consumptions were their a priori voluntary ones (no energy sheds). Thus, the aforementioned pricing model becomes behaviorally efficient and distributes all the financial benefits derived from the energy sheds, namely $G\left(\sum_{c=1}^{C}\overline{x_\iota^k}\right) - G\left(\sum_{c=1}^{C} x_c^k\right)$, to all the communities, in a way proportional to the sheds $\overline{x_c^k} - x_c^k$ that each of them performed.

The energy bill B_i^k of each participating user i during time interval k is then calculated as:

$$B_i^k = \frac{x_i^k}{\sum_{\iota\in C} x_i^k} B_c^k \quad (5)$$

Thus, users share the community's bill in a way proportional to their individual actual consumptions x_i^k.

C. Energy Community Formation Algorithm (ECFA)

There are three criteria that SOCIALENERGY project [12], exploits towards the creation of virtual energy communities. The first one is the similarity factor of the participating users' ECCs. The second criterion (that is more directly related to the potential energy sheds, i.e., the difference between the desired and actual energy consumption) is the flexibility of the participating users. Users with similar flexibility curve perform similar energy sheds when given the same motives. Thus, based on this criterion, ECFA groups users with similar flexibilities towards the development of a fair pricing model. The third criterion that can be used to form the communities is the social correlation of the participating users. The formation of communities according to the social correlation among its members has been found to yield effective behavioral change in many areas. In this work, we demonstrate the formation of communities according to the flexibility criterion and we leave the remaining criteria for future work.

The goal of the ECFA scheme presented in the following is, thus, the grouping of users with similar flexibility. Flexibility of each user could be derived through her/his: i) personal statement, ii) historical data, iii) a behavior model. In this work we assume a parametrized utility function model of the behavior of a user, with parameters corresponding to his/her voluntary consumption and flexibility that are calculated through historical data. In the used model, the convenience of each user i at a time interval k is expressed, in monetary terms, through a utility function$u_i^k(x_i^k, \omega_i^k)$. Intuitively, the utility function defines how much user i values (in the same monetary units the costs are also expressed in, say in \$) the consumption x_i^k at time interval k. The utility function concept comes from microeconomics theory literature [17]-[22] and it is a widely accepted method for the evaluation of pricing models in smart grids.

The form of the utility function is the same for all i and k, and is taken to be a concave and increasing utility function of x_i^k with a constant maximum value of ω_i^k/a after a saturation point (related with $\overline{x_\iota^k}$). A popular choice that we will use in our performance results is:

$$u_i^k(x_i^k, \omega_i^k) = \begin{cases} \omega_i^k * x_i^k - \frac{a}{2} * (x_i^k)^2, & if\ 0 < x_i^k < \omega_i^k/a \\ \frac{\omega_i^k}{a}, & if\ \ x_i^k > \omega_i^k/a \end{cases} \quad (6)$$

In Eq. (6), a is an internal parameter that determines the amount of energy consumption. This representation is able to capture different desired behaviors for different users and different timeslots. The flexibility parameter ω_i^k of user i at time period k is derived through his/her historical data. The user model that we exploit towards this goal is presented in the evaluation methodology. Given a representation of N users, ECFA has to find k communities based on a metric of similarity. Communities are defined so that the similarities between users in the same community are high while the similarities between users in different communities are low. The implementation of ECFA is done through the use of K-means [14] which is one of the most widely used algorithms for clustering. Ease of implementation, simplicity, efficiency, and empirical success are the main reasons for its popularity. In K-Means, the set N of consumers has to be clustered (partitioned) into a set of communities $C = \{c_1, c_2, \dots, c_i\}$. The K-means algorithm finds a partition such that the squared error between the empirical mean of a cluster and the points in the cluster is minimized Eq. (7). Let ω_{c_l} be the mean flexibility of cluster c_i. The squared error between the flexibility of user's in c_i and ω_{c_i} is defined as:

$$\mathrm{E}(c_i) = \sum_{i \in c_i} \left\| \omega_i^k - \omega_{c_i} \right\|^2 \tag{7}$$

The goal of K-Means algorithm is to minimize the overall sum of the squared errors for the set of communities Eq. (8).

$$\mathrm{E}(\mathrm{C}) = \sum_{k \in C} \sum_{i \in c_l} \left\| \omega_i^k - \omega_{c_l} \right\|^2 \tag{8}$$

ECFA's execution starts with an initial partition of k-clusters and assigns patterns to clusters so as to reduce error. The main steps are described below:

1) Start with a decision on the cardinality $|C|=k$, which is the number of communities.
2) Arrange any initial partition that classifies the users into k-communities. First take the first $|C|$ training sample as single-element communities. Then assign each of the remaining (N-$|C|$) training samples to the community with the nearest centroid. Finally after each assignment, algorithm continues by re-computing the centroid of the gaining community.
3) Take each sample in sequence and compute its distance from the centroid of each of the communities. If a sample is not currently in the cluster with the closest centroid, switch this sample to that cluster and update the centroid of the cluster gaining the new sample and the cluster losing the sample.
4) Repeat step 3 until convergence is achieved, that is until a pass through the training sample causes no new assignments.

K-means algorithm in its typical form uses the Euclidean metric for computing the distance between users and community centers. As a result, the optimal allocation is achieved by grouping together consumers with close flexibility parameters. Note that for multi-criteria community formation problem, more sophisticated algorithms are required such as spectral clustering, genetic, etc., (see our related work in [8])

D. Evaluation methodology

In the rest of this section, we present the methodology we used to evaluate the proposed algorithms. Towards this end, we need two major benchmarking elements. The first is a model for the end user and the second a model for the energy generation cost. We highlight that the proposed algorithms (as described earlier) do not make any assumptions on their form. Actually, the utility function used to model the users' behavior in the performance results, does not really have to be known for the schemes to be implemented. A user or a community may simply reply to a price offer by the ESP with an actual consumption without doing any calculations or knowing his/her utility functions. We just exploit these two models and the evaluation methodology in order to evaluate our system through a widely accepted method [16], [17], [18].

The ESP sells energy to its end users, which it buys from the open wholesale electricity market. The cost of the aggregate energy consumed by all users at time interval k is given by $G_k = G\left(\sum_{i=1}^{N} x_i^k\right)$, which is assumed in the literature to be an increasing convex function [16], [19], [20], [21], [22], and is taken in our performance results to be quadratic:

$$G\left(\sum_{i=1}^{N} x_i^k\right) = c \cdot \left(\sum_{i=1}^{N} x_i^k\right)^2 \tag{9}$$

where c is a cost parameter (empirically around 0.02). Eq. (9) represents the cost for the ESP to buy an amount of energy equal to the total demand $\sum_{i=1}^{N} x_i^k$. To develop a pricing model, we also embed the ESP's profit percentage π, so that the total retail market cost of energy at timeslot $k \in H$ is given by:

$$C_k = (1+\pi) \cdot c \cdot \left(\sum_{i=1}^{N} x_i^k\right)^2. \tag{10}$$

We emphasize again that the proposed pricing model does not make any assumption on the form of the energy cost function. C-RTP is general and can be applied with any energy cost function. The choice of Eq. (9) is only for evaluation purposes.

The Community Welfare (CW) of community c is defined as:

$$CW_c^k = \sum_{i \in C} UW_i^k. \tag{11}$$

To also model possible social interactions in the performance evaluation of C-RTP, we assume that users within each community cooperate in order to reduce their energy consumption by a factor δ_c (the percentage of energy reduction in each user in community c) towards the maximization of the community's welfare. After a number of interactions of the two aforementioned steps, C-RTP converges and its outputs are the billed amounts B_i^k and actual consumptions x_i^k for all users $i \epsilon N$ and time slots $k \epsilon H$. Hence, each user adjusts his/her consumption by solving Eq. (12) in order to compute δ value:

$$\delta_c^k = \arg\max_c \{CW_c^k\} \quad . \tag{12}$$

A set of policies able to determine the operation of the communities has been described in our previous work [7]. In this work, we select the aforementioned simplistic policy in order to demonstrate C-RTP. We will focus more on the interaction of them with C-RTP in our future work.

III. Performance Evaluation Results

In order to evaluate the performance of the proposed pricing algorithm, we present and compare C-RTP with the well-known RTP scheme. In our evaluation scenarios, we consider a system with 16 end users. In the first scenario (S1), each one is acting alone (RTP scenario). In the second scenario

(S2A), K-Means algorithm is executed in order to create four community groups with equal number of members in each group (communities of 4 members). Finally, in the third scenario (S2B) K-Means creates eight communities each consisting of 2 members. In order to present a complete approach, simulations were executed under various values of ESP profit percentage π. Additionally parameter ω in the utility function was chosen for each user according to a uniform distribution in the range from 44 to 184 and it is timely invariant. Parameter α was set to 4. Cost parameter c was set to 0.02. The performance of C-RTP and its comparisons with RTP is shown through the demonstration of four widely accepted Key Performance Indicators (KPIs), which are:

- Energy Cost (G) is the amount of ESP cost to purchase the electricity needed in order to meet the consumers requirements. Our proposed pricing scheme attracts users to shed their consumption.
- Aggregate Community Welfare (ACW) is the sum of the welfare of all the communities, in order to present the efficiency of this pricing model in the energy market:

$$ACW = \sum_{c\in C} CW_c^k \tag{13}$$

- Total Welfare (TWF) is defined as the summation of ACW and ESP's profits. It is used in the literature [23], [24] as measure of the total system's optimality:

$$TWF = \mathrm{ACW} + \sum_{c=1}^{C}(B_c^k) - G \tag{14}$$

- ESP profits are defined as the aggregated bill in each of the communities minus the energy cost, in a specific time interval k:

$$ESP\ profits = \sum_{c=1}^{C}(B_c^k) - G \tag{15}$$

Fig. 1 presents the ratio between the system's energy cost under C-RTP and the energy cost under RTP as a function of ESP's profit percentage π. In S2A, C-RTP achieves a cost reduction between 10.5% and 12.2% when compared with RTP (S1). In S2B, C-RTP achieves a cost reduction between 11.5% and 12.5% compared to RTP (S1). This testifies the efficiency of the incentives mechanism of C-RTP.

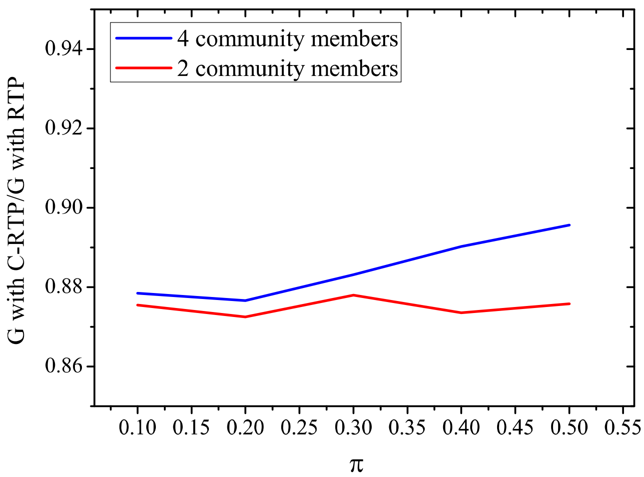

Fig. 1 : Ratio between energy cost G under C-RTP and under RTP as a function of ESP's percentage π

Fig. 2 presents the ratio between the aggregated welfare of the communities in C-RTP and the aggregated welfare of the users in RTP. As we can easily observe, in both comparisons, the difference is always less that 1.2%, meaning that C-RTP affects the welfare of the participating users in a negligible manner.

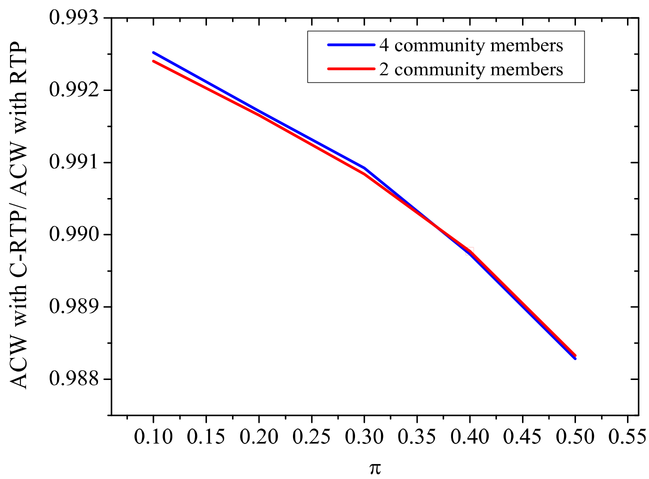

Fig. 2 : Ratio between ACW under C-RTP and AUW under RTP as a function of ESP's profit percentage π

Fig. 3 depicts the ratio between the TWF in C-RTP and RTP again as a function of ESP's profit percentage. As observed, the differences in TWF are negligible (below 0.1%). As a result, our proposed C-RTP achieves a significant cost reduction (10%-15%) without affecting in any case either ACW or TWF.

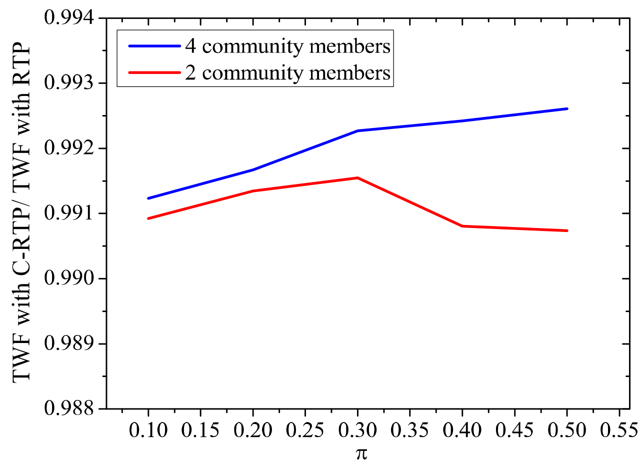

Fig. 3 : Ratio between the TWF under C-RTP and the TWF under RTP as a function of ESP's profit percentage π

Finally, Fig. 4 presents the ratio between the ESP profits (absolute value) achieved under C-RTP and the ESP profits under RTP as a function of the ESP's profit percentage π. Performance evaluation analysis has shown that C-RTP proposed model, does not affect ESP's income in all cases.

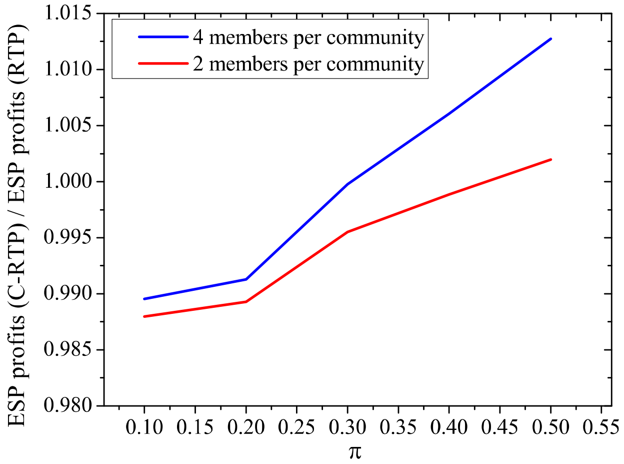

Fig. 4 : Ratio between the ESP profits (absolute value) under C-RTP and under RTP as a function of the ESP's profit percentage π

IV. Conclusions

In this work, we proposed a pricing scheme that groups users into virtual energy communities and offers incentives to them to become more energy efficient. Performance evaluation results show that the proposed Community Real Time Pricing (C-RTP) achieves a reduction in the energy cost of around 10%-15% without sacrificing the welfare of the participating users or the profits of the ESP. Motivated from the these findings, we plan to evolve our work by: i) factorizing other criteria in the formation of communities (additionally to the flexibility of the users), such as their ECC and their social connections, ii) developing more advanced policies that are able to determine how communities will operate, and iii) extending the proposed C-RTP and making it capable to dynamically control energy cost in order to facilitate network stability and/or be used for islanded grid networks, real energy cooperatives and local electricity markets.

Acknowledgment

The work presented in this paper received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 731767 in the context of the SOCIALENERGY project.

References

[1] Ye Yan et. al., "A Survey on Smart Grid Communication Infrastructures: Motivations, Requirements and Challenges", IEEE Communications Surveys & Tutorials, vol. 15, no. 1, pp. 5-20, 2013.

[2] J. S. Vardakas, N. Zorba and C. V. Verikoukis, "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms", IEEE Communications Surveys & Tutorials, vol. 17, no. 1, pp. 152-178, 2015.

[3] B. P. Koirala, E. Koliou, J. Friege, R. A. Hakvoort, P. M. Herder, "Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems", Renewable and Sustainable Energy Reviews, vol. 56, pp. 722-744, April 2016.

[4] FlexiblePower Alliance Network Power Matcher Suite 2015, available online: http://flexiblepower.github.io/why/powermatcher/ [accessed 10.09.2017].

[5] S. Čaušević, M. Warnier, F. Brazier, "Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energy systems", proceedings of the 14th IEEE International Conference on Networking, Sensing and Control, 16-18 May, Calabria, Italy, 2017.

[6] P. Goncalves Da Silva, D. Ilic, S. Karnouskos, "The impact of smart grid prosumer grouping on forecasting accuracy and its benefits for local electricity market trading", IEEE Trans. on Smart Grid, vol. 5(1), pp. 402–410, 2014.

[7] N. Doulamis, A. Doulamis, E. Varvarigos, "Virtual Associations of Prosumers for Smart Energy Networks under a Renewable Split Market," IEEE Transactions on Smart Grid, vol. PP, no. 99, 2017.

[8] Dimitrios J. Vergados et al. , "Prosumer clustering into virtual microgrids for cost reduction in renewable energy trading markets", Sustainable Energy, Grids and Networks 7, pp. 90-103, 2016.

[9] A. J. D. Rathnayaka, V. M. Potdar, T. Dillon, O. Hussain and S. Kuruppu, "Goal-Oriented Prosumer Community Groups for the Smart Grid," IEEE Technology and Society Magazine, vol. 33, no. 1, pp. 41-48, Spring 2014.

[10] K. Ma, G. Hu and C. J. Spanos, "A Cooperative Demand Response Scheme Using Punishment Mechanism and Application to Industrial Refrigerated Warehouses," IEEE Transactions on Industrial Informatics, vol. 11, no. 6, pp. 1520-1531, 2015.

[11] Navigant Research White Paper, "Defining the Digital Future of Utilities: Grid Intelligence for the Energy Cloud in 2030", 2017.

[12] H2020-GA-731767 SOCIALENERGY project, http://cordis.europa.eu/project/rcn/205974_en.html

[13] A. Mani, I. Rahwan, A. Pentland, "Inducing Peer Pressure to Promote Cooperation", Nature Scientific Reports, vol. 3, Article number: 1735, 2013.

[14] Lloyd, Stuart P. "Least squares quantization in PCM." Information Theory, IEEE Transactions on 28.2 (1982): 129-137

[15] W. Tang and Y. J. Zhang, "Online electric vehicle charging control with multistage stochastic programming," in *Proc. IEEE 48th Annu. Conf. Inf. Sci. Syst.*, Mar. 2014, pp. 1–6.

[16] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, "Optimal Real-Time Pricing Algorithm Based on Utiltiy Maximization for Smart Grid", in Proc. of First IEEE International Conference on Smart Grid Communications (SmartGridComm), Gaithersburg, MD, USA, Oct. 2010.

[17] N. Li, L. Chen, and S. H. Low, "Optimal Demand Response Based on Utiltiy Maximization in Power Networks", in Proc. of IEEE Power and Energy Society General Meeting, Detroit, MI, USA, Jul. 2011.

[18] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The Role of Aggregators in Smart Grid Demand Response Markets", IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1247-1257, Jul. 2013.

[19] H. M. Soliman, and A. Leon-Garcia, "Game-Theoretic Demand-Side Management With Storage Devices for the Future Smart Grid", IEEE Trans. on Smart Grid, vol. 5, no. 3, pp. 1475-1485, May 2014.

[20] Z. Wang and R. Paranjape, "Optimal residential demand response for multiple heterogeneous homes with real-time price prediction in a multiagent framework," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–12, 2015.

[21] N. Yaagoubi, and H. T. Mouftah, "User-Aware Game Theoretic Approach for Demand Management", IEEE Trans. on Smart Grid, vol. 6, no. 2, pp. 716-725, Mar. 2015.

[22] Z. Baharlouei and M. Hashemi, "Efficiency-fairness trade-off in privacy-preserving autonomous demand side management," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 799–808, Mar. 2014.

[23] J. Ma, J. Deng, L. Song, and Z. Han, "Incentive Mechanism for Demand Side Management in Smart Grid Using Auction", IEEE Trans. on Smart Grid, vol. 5, no. 3, pp. 1379-1388, May 2014.

[24] P. Samadi, A.-H. Mohsenian-Rad, R. Schober, and V. W. S. Wong, "Advanced Demand Side Management for the Future Smart Grid Using Mechanism Design", IEEE Trans. on Smart Grid, vol. 3, no. 3, pp/ 1170-1180, Sep. 2012.