A Novel Behavioral Real Time Pricing Scheme for the Active Energy Consumers' Participation in Emerging Flexibility Markets

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Abstract – Liberalized electricity markets, smart grids and high penetration of Renewable Energy Sources necessitate the development of novel pricing schemes able to manage energy consumption (energy efficiency services) and harmonize unpredictable and volatile production with ad-hoc consumption (flexibility services). As a result, Energy Service Providers can considerably lower the cost of energy that they purchase from the wholesale market and create new revenue streams, while end users (consumers) can lower their electricity bills and enjoy digital services via the use of the Energy Service Provider's online software platform. Price-based Demand Side Management techniques can trigger the desired behavioral changes and generate novel services and business models for the Energy Service Provider's participation in congestion, balancing, peer-to-peer and other emerging flexibility markets. As we argue in this paper, the energy pricing schemes proposed so far (e.g. Real Time Pricing) do not provide strong enough financial incentives to consumers to modify their energy consumption habits (which leads to reduction of energy cost), as they are unfair and thus unable to effectively trigger behavioral changes and enter competitive flexibility markets. Based on this observation, we develop a Behavioral Real Time Pricing scheme, which offers an easily adjustable level of financial incentives to participating users by fairly rewarding the ones that make desirable behavioral changes in the way they consume electricity. Performance evaluation results demonstrate that the proposed billing scheme affects the behavior of the consumers much more efficiently than the traditional Real Time Pricing mechanism, outperforming the latter in all widely adopted metrics. Our billing mechanism is able to simultaneously: i) significantly reduce energy cost compared with Real Time Pricing (10%-30%), ii) slightly increase end users' welfare (2%-4%) and iii) ensure fairness in the allocation of financial benefits among the end users. All these constitute our proposed billing mechanism much more competitive in the flexibility markets.

Keywords: Smart grid, demand side management, dynamic pricing, flexibility markets, behavioral change, energy efficiency[1]

I. Introduction

Conflicts of interest: All authors declare no conflicts of interest.
*Color should be used for all figures

The aging infrastructure of the traditional power grid, the projected growth in global electric energy demand [1], [2], the increasing global environmental concerns and the circumstances in global economy [3] have triggered an increasing interest in *energy efficiency* [4]. The aforementioned developments have also motivated a high penetration of Renewable Energy Sources (RES) into the grid. The latter, however, results in high levels of uncertainty and variability in the energy production rate. Demand Side Management (DSM) is recognized as a promising tool able to improve energy efficiency and network stability. DSM techniques are deployed in order to incentivize electricity consumers to modify their Energy Consumption Curves (ECCs) in a more energy-efficient way, aiming to achieve a continuous and steady balance between production and consumption (cf. balancing market). Furthermore, the liberalization of electricity markets and the emergence of innovative business models ([5], [6], [7], [8]) boost the importance of the trade-off between the quality of services (QoS) that an Energy Service Provider (ESP) offers and its profitability margins with respect to the new revenue streams that it can create. Therefore, the development of advanced DSM strategies, able to efficiently deliver more competitive energy services, is of a great importance.

Energy consumers that participate in DSM programs take actions that can be classified into two categories: i) *load shedding,* by either adopting energy efficiency policies or following a more conservative consumption pattern, and ii) *load shifting*, by operating flexible appliances in off-peak hours. Both of the aforementioned strategies elevate the level of discomfort for the consumers. Therefore, for most consumers, financial incentives are key to the design of effective DSM programs.

Intelligent energy pricing schemes are automated DSM strategies, which try to incentivize electricity consumers towards a consumption pattern that provides an attractive trade-off between their desired ECC and the one that is cost-efficient for the power system [9]. As analyzed in the next section, recent research has focused on the development of pricing schemes with the objective to efficiently schedule flexible loads. Historically, the energy pricing models started with flat electricity tariffs. Under this scheme, consumers are charged with an identical and time invariant price per energy unit and therefore, they are not really motivated to consume electricity in an efficient way. This leads to over-investments by the DSOs and/or TSOs in order to afford to meet the load demand and ensure grid stability [10]. The pricing scheme of Inclining Block Rates (IBR) was a first attempt to interact with the electricity consumers' behavior. In the IBR scheme, the price per unit increases with the total energy that the user consumes, creating a barrier that prevents the over-use of energy and consequently an power shortage and/or network failures. The next step was the Time-Of-Use (ToU) pricing method, which motivates consumers to shift loads into low pricing hours; however, a priori set prices do not reflect the real-time needs of the grid. Hence, it may result in congestion issues during the low-price hours. Real – Time Pricing (RTP) schemes ([11], [12], [13], [14], [15]) have been proposed in order to directly connect the actual energy production, transmission and distribution costs with the retail energy price. On the other hand, RTP schemes still suffer from the 'tragedy of the commons' phenomenon [16], in which a consumer that changes her ECC (behavioral change in energy consumption) generates a benefit for the entire system. In the average case, only a small portion of this benefit is returned to her, while the major part of it is shared among all the consumers. In this regard, RTP schemes are not fair and do not efficiently incentivize behavioral changes. This issue is a major motivator for the design of our proposed Behavioral RTP (B-RTP) scheme towards efficiently engaging end users in DSM programs.

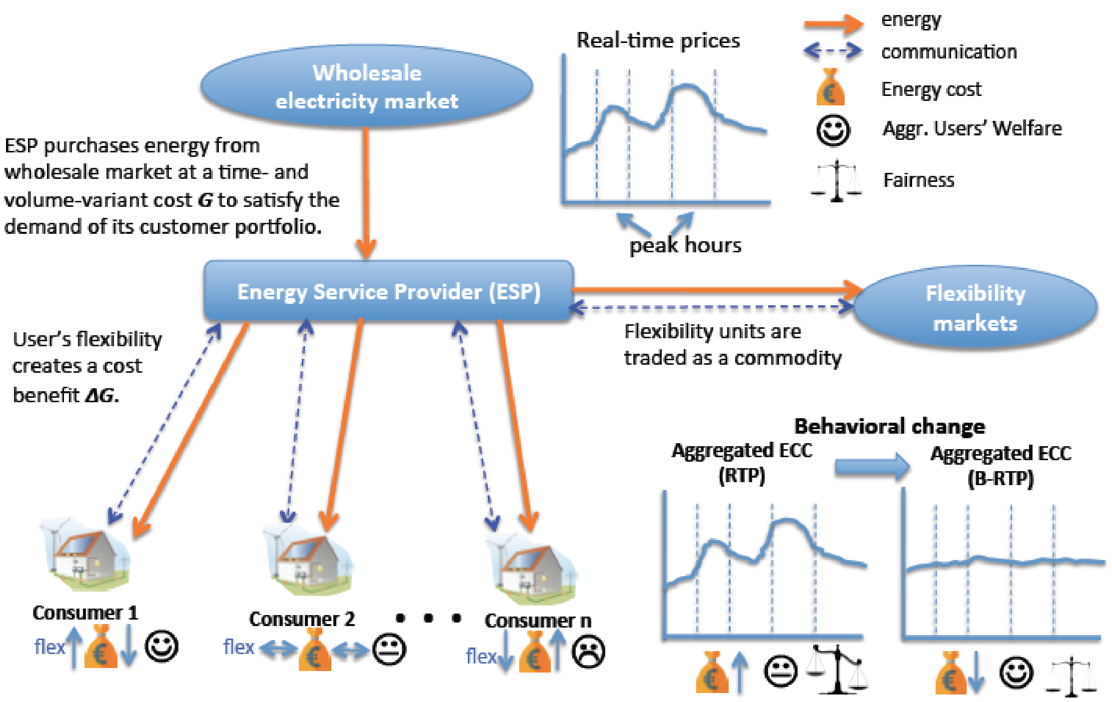

Figure 1: Proposed architecture and business model for the energy flexibility units trading

In Fig. 1, the role and use of the proposed B-RTP scheme for facilitating the trading of DSM units in flexibility markets is illustratively explained. In the assumed business model, the ESP purchases energy from the wholesale electricity market at a time- and volume-variant cost G in order to satisfy the demand of its customer portfolio (i.e. energy consumers). On the other hand, aggregated users' flexibility (behavioral changes) can create a cost reduction ΔG. Subsequently the ESP can trade its ability to control the demand (e.g. reduce energy cost) as a commodity in various types of flexibility markets (e.g. congestion, balancing, voltage control, frequency control markets, etc.). This amount of ΔG can be fully returned back as a reimbursement/discount to the end users or a fraction of ΔG can also be used to increase the ESP's profits. In this paper, we assume the former case for simplicity reasons.

The objective of the proposed B-RTP scheme is the reduction of the energy system's cost without deteriorating the users' quality of experience (or else, aggregated users' welfare). Moreover, B-RTP has to fairly allocate the cost reduction benefits among the users that create them, which is very important for the business success of the proposed pricing scheme. According to the extensive performance evaluation results presented in section V for the proposed personalized energy billing mechanism, B-RTP achieves an energy system's cost decrease from 10% to 30% depending on the cost of energy in the wholesale market and the various users' flexibility levels. For the majority of the simulation scenarios, the users' quality of experience is not affected at all. Actually, in some cases, it is enhanced by a factor of 2-4%. Of course, in extreme simulation scenarios, in which flexibility need is crucial for the network's operation, the quality of experience may be slightly deteriorated (but again within acceptable levels) at the expense of much better financial benefits returned back to the end users. Finally, B-RTP achieves to fairly allocate the financial benefits to all end users according to the degree of each one's participation in the total energy system's cost decrease. What's more interesting is that the ESP can dynamically configure the trade-off between the afore-mentioned Key Performance Indicators (KPIs) in order to achieve its optimal participation in the flexibility markets (cf. parameter 'γ').

The remaining of this paper is organized as follows. In Section II, we briefly discuss the related work and we highlight the contributions of this paper. In Section III, we describe the proposed system model. In Section IV, we propose our innovative B-RTP scheme. In Section V, we evaluate our proposed billing scheme through extensive simulations, using the RTP scheme as a benchmark. Finally, in Section VI we conclude and discuss future work.

II. Related Work

In the context of open electricity markets and progressive business models in the smart grid sector, a pricing scheme has to fulfill specific requirements (by achieving an attractive trade-off) such as: i) the consumer's satisfaction (or else user's welfare), ii) the stability/efficiency of the power grid (or else energy system's cost), and iii) fairness (or else ensure that each user receives a financial reward, which is exactly proportional to her contribution in the energy system's cost decrease).

The first requirement is widely known as user's welfare and is determined as the satisfaction (level of comfort) of user towards a given time instance of her ECC, minus the bill she has to pay for it. The users' welfare achieved by a DSM program determines the willingness of a user to participate in the DSM program. In other words, it demonstrates which program leads to more competitive services in an open energy market. In [11], [17], [18] and [19] users' welfare is considered as the system's objective. In [11], a distributed algorithm is proposed, where users shed their consumption attempting to maximize their welfare as a response to price signals from the ESP. In [17] and [19], game-theoretic approaches are used, in which users shift or shed their loads with the objective to maximize their own welfare, while the ESP sets the real-time energy prices based on users' decisions. [18] considers users that can operate both shiftable and curtailable loads with the same objective; however, prices are set a priori and the interaction between the ESP and the end users is not considered. Our paper's novelty is that we examine user's welfare together with the decrease of energy system's cost and fairness KPI.

The second requirement expresses the capability of a pricing model to incentivize energy consumers to adopt ECCs that minimize the production and distribution cost of the energy that they consume. In our case, this cost is the one that the ESP pays to the wholesale market in order to purchase the required energy to satisfy the aggregated ECC (i.e. demand) of its users. Therefore, this requirement is denoted as behavioral efficiency and it reflects which pricing model is able to fulfill the objectives that energy producers, DSOs, TSOs and BRPs set. In [20], [21], [22], [23] and [24] behavioral efficiency is evaluated in terms of reduction of the total energy cost. In [21], an online Electric Vehicle (EV) charging scheduling algorithm is proposed in order to minimize total energy cost, while in [22] an optimization-based algorithm is proposed for the operation of different classes of devices with the objective to minimize the energy cost without sacrificing users' comfort. Researchers in [23] consider both energy cost and users' welfare as their system's objective, while Soliman et al. in [24] present a game-theoretic approach to analyze the interaction between end users and the ESP in the presence of storage devices. The objective of the model is the minimization of energy cost. In [25], users schedule their consumption in order to reduce the system's Peak-To-Average Ratio (PAR), which is linked to system's energy cost. On the other hand, users' comfort is not taken into consideration. Again, our proposal goes one step further by considering all three above-mentioned KPIs at the same time.

The third requirement is fairness. It refers to how fairly the system's energy savings, which result from the behavioral changes of the participating users, are allocated among them. Baharlouei et al. in [14] propose a pricing model based on the principle that the users' bills should be analogous with their contribution to the system's energy cost reduction. Finally, the design of a pricing scheme should take into consideration the profitability of the ESP, if the business model facilitates this option [12], [26]. However, these fairness-related works admit that they sacrifice energy system's cost decrease in order to achieve their objective, which is a problem that our proposed scheme addresses, too.

In the majority of the aforementioned works, the sole objective is social welfare maximization, which is defined as the users' comfort minus the system's cost (or user welfare plus the ESP's profits). In these pricing schemes, social welfare maximization generally comes with budget revenue (profit) for the ESP, which is not the case of the business model assumed in this paper. This paper considers cases, in which ESPs sell energy with (close to) zero profit to retail markets, such as: i) open markets with perfect competition [27] as analyzed in [28], ii) energy cooperatives [29] or islanded energy sharing communities [30], where energy prosumers share their energy in order to ensure the energy autonomy of the community, and iii) ESPs that participate in a flexibility market [5] and provide profitable flexibility services to DSOs, TSOs and BRPs. Furthermore, in contrast with the majority of related work, we consider that users are not just price takers; however they act as price anticipators. That is, they can have an impact on their energy bills exploiting their flexible appliances.

Studies that propose DSM algorithms with active user participation use a user model in order to evaluate their algorithms' performance. Many works ([11], [12], [31], [32], [33], [34], [35], [36], [37]) exploit the assumed user model in order to design model-specific pricing schemes leveraging analytic solutions. However, the electricity consumer model is still unclear for the research community because there are no public large scale data from field trials. A comprehensive critique of this approach is presented in [38], [39]. In this paper, we propose a discriminative pricing scheme based on each user's behavior, which preserves efficiency in terms of social welfare, while at the same time achieves a budget-balanced system (or profits close to zero), fairness and reduced system cost. The proposed algorithm, however, is not tuned to any specific user model. Rather, it performs equally well for any user model that fulfills some mild assumptions. These attributes make the proposed B-RTP an advantageous scheme for all above-mentioned business cases. Finally, it fits very well the latter case, where an ESP participates in a flexibility market, as it is able to motivate its users (customers) to adjust their ECCs according to the needs of the market while keeping them well-satisfied. To the best of our knowledge, no other research work has dealt with this type of emerging business model considering at the same time the three above-mentioned KPIs. Conclusively, the contribution points of this paper can be summarized as follows:

- A novel non-profitable energy pricing scheme, referred to as Behavioral Real-Time Pricing, which exploits as incentives its high levels of fairness to remarkably reduce the aggregated energy cost, while simultaneously slightly increasing user's welfare. B-RTP quantifies the system cost reduction achieved by each end user's load shifts and curtailments and rewards her accordingly.
- A mechanism that parameterizes the proposed scheme, enabling it to dynamically adjust the degree of incentives. Thus, it indirectly controls the aggregated energy cost. This gives ESP the opportunity to dynamically select the best trade-off among the aforementioned three requirements according to its dynamically changing business needs.
- A holistic comparison between the proposed B-RTP and a non-profit version of an existing RTP scheme that is widely adopted in the literature. We demonstrate that B-RTP scheme achieves a more attractive trade-off among the aforementioned requirements by reducing the system's cost, while preserving social welfare efficiency and enhancing fairness.

III. System Model

We consider a smart community, which consists of a set of electricity users (denoted as $\boldsymbol{N}$) and an ESP. An electricity consumer can be a single smart home or a group of smart homes acting as a single unit. Each user $i \in \boldsymbol{N}$ is equipped with advanced Smart Meters that monitor her appliances' ECCs and an Energy Management System (EMS) that schedules her energy consumption over the scheduling horizon, according to the preferences that she sets. We do not consider price-taking consumers as in [18]; on the contrary, users interact with the ESP in order to reach an agreement on the energy consumption schedules and energy prices. A communication network lies on top of the electric grid, enabling the message exchange between the users and a Price Controller (PC) installed at ESP's premise. The PC receives each user's *i* aggregate consumption and sends back to the users' EMSs their energy bills. As we later analyze, our proposed architecture includes limited information disclosure from the energy consumers and thus preserves their privacy by following the same data exchange model as in [40].

In order for an ESP to evaluate each end user's behavioral change, 2 use cases are considered: i) Users' "base" ECC is a priori known (before the behavioral changes that B-RTP will incentivize) and ii) Users' "base" ECC is unknown. By "base", we mean the natural/voluntary (unforced) consumption behavior of a user, in the absence of incentivized time varying penalties or rewards. B-RTP applies to the first use case. Examples of this use case are:

- Working environments in which operations that include power consumption are scheduled and invariant from one day to another.
- Direct contract between ESPs and a large industrial client with standard ECCs.

- Aggregated consumption patterns of groups of users (which are accurate enough because of statistical multiplexing).

The monetary gains from the reduction of total energy cost (ΔG) may be fully given as discounts to the end users, or other market stakeholders (e.g. ESPs) may acquire a certain fraction as their profit. In addition, stakeholders that participate in flexibility markets ([32]) obtain additional revenues from these markets for their ability to control energy consumption/cost. In this work, we consider the demanding subcase of a highly competitive environment (as in [28, Chapman]), where discounts are fully given to end users and revenues from flexibility markets are close to zero; the relaxation of this assumption is left as future work.

Next, we present the user model and the energy generation cost model. Both models are widely adopted in the literature. Their purpose is only to facilitate the evaluation of the proposed B-RTP scheme through the comparison between B-RTP and RTP. Note that they do not constitute a novelty aspect, but rather emphasize that the proposed B-RTP is utility-agnostic and thus can be applicable in any type of user and cost modeling. Finally, without harm of generality, we consider a discrete-time model with a finite horizon that models the scheduling period ***H***. Each period is divided into *T* timeslots of equal duration.

A. Demand Side Model

Each user $i \in \boldsymbol{N}$ owns a set $\boldsymbol{D_i}$ of household devices, and each device $d \in \boldsymbol{D}_i$ consumes energy $x_{i,d}^t$ at time $t \in \boldsymbol{H}$. The total amount of energy, that all devices in $\boldsymbol{D}_i$ consume at time *t,* is denoted as x_i^t. According to the literature ([12], [18], [41]) a user's devices can be categorized into three categories with respect to their load flexibility: *curtailable*, *shiftable* or *non-adjustable*.

1. Curtailable Loads

This category of loads includes appliances such as: heating, ventilation, and air conditioning (HVAC) system, building lights with adjustable volume, etc. We denote by $\boldsymbol{D}_{c,i} \subseteq \boldsymbol{D}_i$ the set of curtailable appliances of user *i*. For each device $d \in \boldsymbol{D}_{c,i}$, each user $i \in \boldsymbol{N}$ a priori declares a desired consumption schedule $\widetilde{x_{i,d}} = \left\{\widetilde{x_{i,d}^t}, t \in \boldsymbol{H}, d \in \boldsymbol{D}_{c,i}\right\}$ according to her preferences, and a minimum consumption level $\underline{x_{i,d}^t}$ $, t \in \boldsymbol{H}, d \in \boldsymbol{D}_{c,i}$ (see Eq. (1)). User's satisfaction in every time slot t depends on the amount of energy that a curtailable device actually consumes, denoted as $x_{i,d}^t$, and on how close it is to the desired consumption $\widetilde{x_{i,d}^t}$. Therefore, user *i* attains a utility $U_{i,d}^t(x_{i,d}^t)$ in time interval *t* when her device *d* consumes $x_{i,d}^t$, which varies according to her lifestyle and preferences.

$$\underline{x_{i,d}^t} \leq x_{i,d}^t \leq \widetilde{x_{i,d}^t} \tag{1}$$

In order to have a benchmark for the evaluation of B-RTP, we use the concept of utility function, drawn from the fields of Microeconomics [42], which models the end users' preferences regarding the operation of a device. In the case of curtailable devices, it is reasonable to assume that the users' utility function is increasing (the more a user consumes, the more utility she perceives) and concave (the more a user consumes, the less the incremental added utility is). This approach is also in line with the vast majority of the literature (e.g. [11], [31], [43], [44]) where a quadratic form is usually considered for the utility function, expressed as:

$$U_i^t(x_i^t, \omega_i^t) = \begin{cases} \omega_{i,d}^t \cdot x_i^t - \frac{a}{2} \cdot (x_i^t)^2, & if \;\; 0 < x_i^t < \frac{\omega_{i,d}^t}{a} \\ \frac{(\omega_{i,d}^t)^2}{2 \cdot a} & , \;\; if \;\; x_i^t > \frac{\omega_{i,d}^t}{a} \end{cases} \tag{2}$$

In Eq. (2), *a* and ω_i^t are predetermined parameters. ω_i^t denotes the responsiveness of user *i* to financial incentives (*flexibility*) at time interval *t* in terms of reduction of her energy consumption, while parameter a expresses how the rate of change of user's utility changes as consumption changes. Another utility function, that is used by the literature ([19], [45]), exploits $\widetilde{x_i^t}$ in order to calculate the utility that user attains:

$$U_i^t(x_i^t) = \begin{cases} -\left(x_i^t - \widetilde{x_i^t}\right)^2, & if \; 0 \le x_i^t \le \widetilde{x_i^t} \\ 0, & if \; x_i^t > \widetilde{x_i^t} \end{cases} \tag{3}$$

In order to combine the advantages of the two aforementioned functions, we use a utility function, which is mathematically expressed as:

$$U_{i,d}^t(x_{i,d}^t) = \begin{cases} U_{\max,i,d}^t - \omega_{i,d}^t \cdot \left(x_{i,d}^t - \widetilde{x_{i,d}^t}\right)^2, & if \; 0 \le x_{i,d}^t \le \widetilde{x_{i,d}^t} \\ U_{\max,i,d}^t \;\; , & if \; x_{i,d}^t > \widetilde{x_{i,d}^t} \end{cases} \tag{4}$$

$U_{\max,i,d}^t$ denotes the maximum user satisfaction concerning appliance d, i.e. the one achieved when she consumes her desired load. The proposed utility function of Eq. (4) is a composition of the two aforementioned functions and is able to: i) capture the heterogeneity in the flexibility among participating users, just as Eq. (2) does through ($\omega_{i,d}^t$) and ii) explicitly correlate maximum user's satisfaction with her desired consumption $\widetilde{x_{i,d}^t}$, as utility function of Eq. (3) is also able to do. In Eq. (4), $\omega_{i,d}^t$ is once again a predetermined parameter that captures the flexibility of user *i* concerning appliance d in time slot *t.* More specifically, the lower the value of parameter $\omega_{i,d}^t$, the more tolerant user will be towards a particular change in her desired energy schedule of device *d*. Fig. 2 depicts user's *i* utility at time slot *t* as a function of $x_{i,d}^t$ for a given $U_{\max,i,d}^t$ and different values of $\omega_{i,d}^t$.

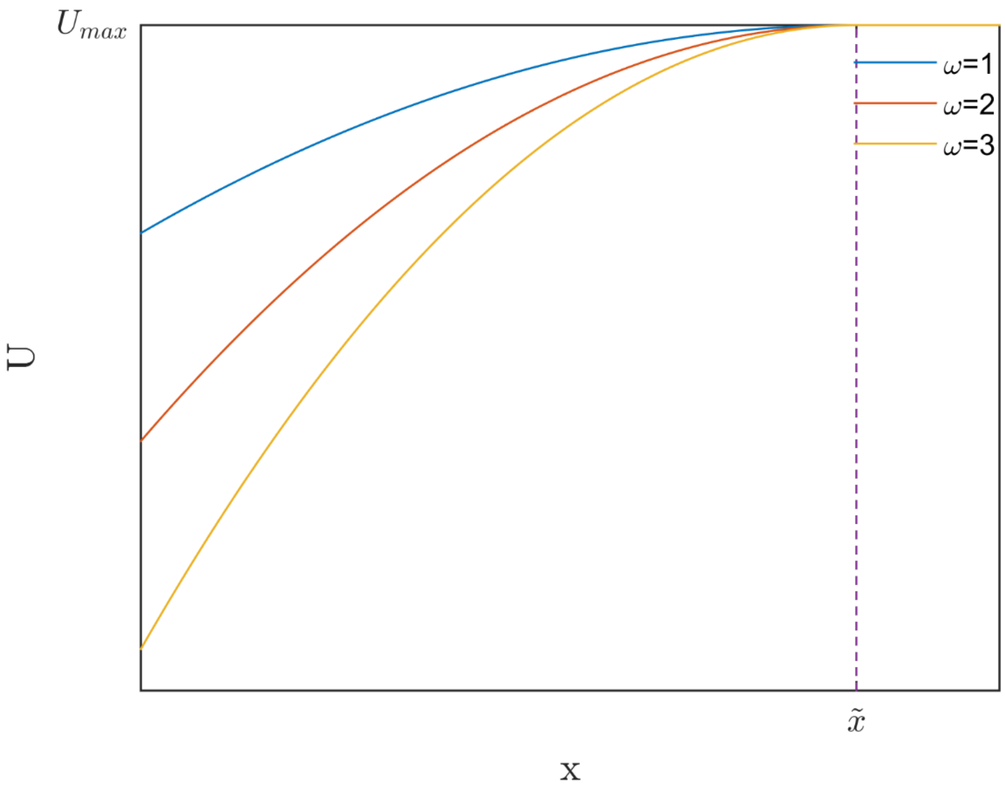

Figure 2: User's *i* utility in timeslot *t* as a function of her/his energy consumption for various flexibility levels

2. Shiftable Loads

This category of loads includes appliances that can shift their consumption according to user's preferences. Appliances such as: EVs, the dishwasher, the washing machine and the clothes dryer can be considered available for consumption shift. We denote by $\boldsymbol{D_{s,i}}$ the set of shiftable appliances of user *i*. For this type of appliances, energy consumer sets a desired operating schedule $\widetilde{x_{i,d}^{t}}, t \in \widetilde{\boldsymbol{H}_{\boldsymbol{s}}}$, where $\widetilde{\boldsymbol{H}_{\boldsymbol{s}}} = [\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}]$ is a time interval where $\widetilde{t_{i,d}^{a}}$ is the timeslot at which it is desirable for the device to start and $\widetilde{t_{i,d}^{b}}$, is the timeslot at which *d* normally finishes its task if it starts operation at $\widetilde{t_{i,d}^{a}}$. Additionally, user *i* sets a deadline $t_{i,d}^{l}$, which is the latest time by which the task of device *d* should be completed. Thus, regardless of the shifts that will take place, the total energy consumption of user's i device $d \in \boldsymbol{D}_{s,i}$ must reach a certain energy threshold $E_{i,d}$ by $t_{i,d}^{l}$, that is,

$$0 \le x_{i,d}^{t} \le E_{i,d}\ , \quad \forall t \in \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right] \tag{5}$$

$$\sum_{t=\widetilde{t_{i,d}^{a}}}^{t_{i,d}^{l}} x_{i,d}^{t} = E_{i,d}, \qquad \forall i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}} \tag{6}$$

Therefore, regarding user's *i* shiftable loads, we can define a feasible scheduling set X_i that is,

$$X_i = \{x_i | \sum_{t=\widetilde{t_{i,d}^{a}}}^{t_{i,d}^{l}} x_{i,d}^{t} = E_{i,d}, \quad \forall d \in \boldsymbol{D_{s,i}},$$

$$0 \leq x_{i,d}^{t} \leq E_{i,d}\,, \qquad \forall t \in \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right],$$

$$x_{i,d}^{t} = 0, \quad \forall t \in H \backslash \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right] \} \tag{7}$$

We assume that each user is fully satisfied when the operation of her device $d \in \boldsymbol{D}_{s,i}$ does not deviate from her desired energy schedule $\widetilde{\boldsymbol{x_{i,d}}} = \left\{\widetilde{x_{i,d}^{t}}, t \in \widetilde{\boldsymbol{H_s}}\right\}$, where $\widetilde{\boldsymbol{H_s}}$=[$\widetilde{t_{i,d}^{a}}$, $\widetilde{t_{i,d}^{b}}$]⊆ $\boldsymbol{H_s}$ and $\boldsymbol{H_s} = [\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}] \subseteq \boldsymbol{H}$. The degree (monetary value) of each user's *i* dissatisfaction for every unit of energy that a shiftable device d consumes in any other time slot ($t \in \boldsymbol{H_s} \backslash \widetilde{\boldsymbol{H_s}}$) depends on user's individual lifestyle and preferences. In the literature, this particular behavior of users is modeled by a disutility function ([12], [17], [46], [43], [47], [48], [49]). In this paper, we assume that user's dissatisfaction increases as her shiftable devices consume more energy at later hours in $\boldsymbol{H_s}$**,** which intuitively means that her waiting time increases. Thus, we exploit the utility function used in [43], where user's *i* dissatisfaction for her/his device d is given by:

$$DU_{i,d} = \sum_{t \in \boldsymbol{H_s}} \frac{(\delta_{i,d})^{t-\widetilde{t_{i,d}^{b}}} \cdot x_{i,d}^{t}}{E_{i,d}}. \tag{8}$$

In Eq. (8), $\delta_{i,d} \geq 1$ is an adjustable control parameter. The higher the value of $\delta_{i,d}$ the higher the dissatisfaction of user *i* for a given change in her desired energy schedule of device *d* will be. In other words, the lower the value of parameter $\delta_{i,d}$, the more responsive user *i* will be to price incentives. As we did in the case of curtailable loads, we once again note that this utility function (Eq. 8) is used only for evaluation purposes and the proposed B-RTP is transparent to any utility function that fulfills the following properties:

i. Non-decreasing functions. Users' satisfaction increases with power consumption level until the latter reaches a certain threshold ($\tilde{x}$):

$$\frac{\partial U}{\partial x} \geq 0 \tag{9}$$

ii. The marginal utility (Eq. (10)) that users perceive is a non-increasing function:

$$V(x) \equiv \frac{\partial U}{\partial x} \tag{10}$$

$$\frac{\partial V}{\partial x} \leq 0 \tag{11}$$

In any other case, convex optimization may not be applicable to solve the user's problem, but rather some other heuristic algorithm (e.g. simulated annealing), which is out of the scope of this paper.

3. Non-adjustable Loads

Each user i a priori declares which of her devices fall into this category. These loads have predetermined consumption schedules and are not controllable by the EMS. We denote by $\boldsymbol{D_{f,i}}$ the set of the devices that user i categorize as non-adjustable. Examples of this category of appliances are: refrigerator, freezer, TV, etc. For non-adjustable loads, we should have:

$$x_{i,d}^{t} = \widetilde{x_{i,d}^{t}} \;, \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}, d \in \boldsymbol{D_{f,i}}. \tag{12}$$

B. Energy Cost Model

In the literature [11], [12], [14], [15], [26], [31], [50], [51], in order for the pricing models to be evaluated, an increasing convex function *G(x)* is often adopted to (approximately) model the cost of energy that comes from conventional generation. Piece-wise linear functions and quadratic functions are two examples of cost functions. In this paper, we use a quadratic energy cost function, the mathematical expression of which is given by:

$$G^{t} = G\left(\sum_{i=1}^{N} x_{i}^{t}\right) = a \cdot \left(\sum_{i=1}^{N} x_{i}^{t}\right)^{2} + b \cdot \left(\sum_{i=1}^{N} x_{i}^{t}\right) + c, \tag{13}$$

where $a > 0,\ b, c \geq 0$ are predetermined parameters that depend on the energy generators characteristics. This cost function models either the cost of the ESP to purchase the necessary energy units from the wholesale electricity market, or the actual cost of the ESP to produce energy by operating its own generation units.

IV. Proposed system

We consider electricity consumers (users) that participate in a DSM program (which is modeled as a game). We suppose users are price anticipators, i.e. they are aware of the billing mechanism and they consider the impact of their actions on their electricity bills. Their objective is to maximize their payoff. User's i payoff is defined as her individual welfare, which equals to the total utility attained, when her schedulable appliances consume a certain amount of energy (as analyzed in the previous section) minus her energy bill B_i given by Eq. (14). Thus, each user's EMS calculates her energy consumption schedule by solving Eq. (15), and then informs ESP about the updated consumption schedule x_i. ESP, in turn, sets the energy prices so as to achieve an attractive trade-off among the three requirements that have been described in Section II. Its primary goal is to motivate consumers to change their ECCs through a *fair* billing scheme in order to reduce the *total energy cost* without sacrificing efficiency in terms of *social welfare.* Social Welfare (*SW*) is defined as the aggregate users' comfort minus the total energy cost (Eq. (16)). Users and ESP repeat the aforementioned steps until the process converges to the Nash Equilibrium (NE).

$$W_i = \sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}} \left(DU_{i,d}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right)\right) - B_i \tag{14}$$

$$x_i = \arg\max \quad W_i \tag{15}$$

Subject to (1), (7), (12)

$$SW = \sum_{i=1}^{N} \left(\sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}} DU_{i,d}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right)\right) - \sum_{t=1}^{H} G^{t} \tag{16}$$

In what follows, we start by presenting the RTP scheme and follow with the description of our proposed B-RTP scheme. The RTP scheme will be used in Section V as a benchmark, in order to evaluate the performance of B-RTP.

1. State-of-the-art Real-Time Pricing (RTP) scheme

In the initial phase of the RTP ([12], [15]) algorithm, ESP collects the desired schedule $\widetilde{x}_i$ of each user *i* from their EMSs, and calculates their nominal energy bills $\tilde{B}_{i,RTP}$, $\forall i \in \boldsymbol{N}$. In order to do so, ESP exploits Eq. (17) to calculate the price (average cost) per unit of energy at each time interval *t* as

$$\rho^t = \frac{G(\sum_{i=1}^{N} x_i^t)}{\sum_{i=1}^{N} x_i^t} \quad . \tag{17}$$

ESP, through the communication infrastructure, informs its customers about the energy bills, calculated by

$$B_{i,RTP} = \sum_{t=1}^{N} \rho^t \cdot x_i^t \tag{18}$$

Eq. (17) corresponds to a non-profit version of RTP ([12], [15]). In [12], it is proven that social welfare is maximized when ρ^t is set to the marginal cost of energy, (i.e. $dG(\sum_{i=1}^{N} x_i^t)/d(\sum_{i=1}^{N} x_i^t)$). However, in this case, social welfare maximization comes with budget revenue, which violates the budget-balance property of the assumed business model (cf. Section II). Thus, in order to evaluate B-RTP, we exploit a non-profit RTP version according to Eq. (17). The algorithm of RTP scheme is summarized in Table I, where *k* is an index for the algorithm's iterations.

TABLE I. ALGORITHM FOR THE CALCULATION OF THE ENERGY BILLS AND THE ENERGY CONSUMPTION SCHEDULES IN RTP

1	**Initialization**: $k = 1$, $x_i^k = \widetilde{x_i^k}$, $B_{i,RTP}^k = \tilde{B}_{i,RTP}$
2	**Repeat**
3	$k \rightarrow k+1$
4	**For** each user $i \in \boldsymbol{N}$
5	Receive $B_{i,RTP}^k$ from ESP
6	**Repeat**
7	Update x_i^k
8	$B_{i,RTP}^k$ is updated through (17), (18)
9	Calculate W_i^k using (14)
10	**Until** Reach solution of (15) subject to (1), (7) and (12)
11	**End for**
12	Calculate $divergence = max\left\|x_i^{t,k+1} - x_i^{t,k}\right\| \quad \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}$
13	**Until** $divergence < desired\ accuracy$
14	**End**

2. Proposed Behavioral Real-Time Pricing (B-RTP) scheme

B-RTP model is a hybrid billing mechanism that is able to take full advantage of users' flexibility. This is achieved through a personalized billing policy, which rewards consumers' behavioral change (i.e. ECC adjustment) in a fair manner. In more detail, consumers receive a discount in their energy bill, which is equal or proportional to their contribution to the total energy cost reduction. Users that do not change their ECCs do not receive similar treatment and may even be penalized in cases of emergency situations, in which a significant energy cost reduction is demanded (e.g. network congestion, lack of energy in islanded mode, etc.). In these cases, as our evaluation results will show, ESPs using B-RTP are able to participate in various types of flexibility markets ([5] [6]) without sacrificing user's welfare and fairness.

As in RTP algorithm, in the initialization phase of B-RTP users set their desired consumption schedules $\widetilde{x_i}$ (desired ECC). Based on those, ESP calculates $\widetilde{B}_{i,RTP}$, $\forall i \in \boldsymbol{N}$, using Eqs. (17) - (18), and communicates them to the users. Each user, in turn, having knowledge of the method of her energy bill's calculation, keeps updating her ECC until she reaches the solution of Eq. (15). This process is repeated (as depicted in Table I) until its convergence to the final (actual) ECCs and energy bills. As it is obvious from the above, the valuation of an ECC for a specific user *i* (e.g. the evaluation of RTP price from Eq. (17)) is not a standalone process. The bill of each user *i* depends on the ECCs of the other users in set *N*, as Eq. (18) depicts for RTP. RTP scheme, as well as other DSM algorithms (e.g. [12], [14], [31]), considers that users determine their ECCs sequentially and subsequently, ESP determines the valuation of the ECCs until the convergence of this iterative process. In more detail, in each and every iteration of the aforementioned process, a user *i* is implicitly but adequately informed (through the billing system) about the decisions (ECCs) of the users that acted before her and exploits this information to update her x_i^t.

In the case of B-RTP, as far as the shiftable loads are concerned, this sequential process creates an advantage for the users who act first over those who act later. For example, two equally flexible users with identical ECCs would be similarly responsive to a specific financial incentive given by the ESP. However, if the one that acts first shifts a load from a peak-hour to a low-cost time interval, the second user will not be able to do the same, as that would lead to a reverse peak. Thus, the first user will get a discounted energy bill, while the second user will not. Consequently, users' order of action plays a major role in the final energy schedules and energy bills. To overcome this problem, we exploit and enhance [52], in which users act in parallel and therefore they decide their actions without knowing what the others do in each iteration of the aforementioned process. Thus, in every iteration *k* of B-RTP, all users, based on the same information on billing mechanism, calculate their energy schedule by solving Eq. (15) simultaneously. This approach, may temporarily create reverse peaks, since every user, in order to achieve a larger total cost reduction and receive a larger discount in her energy bill, shifts her shiftable loads to low–cost hours. In order to overcome this problem, in each iteration *k*, we impose a restriction in the changes that users are allowed to make in their energy schedules. In more detail, the updates are done so that shifts are done in an incremental way, satisfying,

$$\left|x_i^{t,k} - x_i^{t,k-1}\right| < \theta^k \cdot x_i^{t,k-1}, \tag{19}$$

where $\theta^{\kappa} < 1$ is a parameter that sets the upper bound of the volume of shift that a user can make in a certain step *k* of B-RTP. If there is a reduction in total energy cost after users' decisions(i.e. no peak shifting), θ^{k+1} will remain the same as in iteration *k*. Otherwise, if the reduction of the total cost of the system is negligible, i.e. $G^{k+1} > G^k * (1-\varepsilon)$ for some small $\varepsilon > 0$, B-RTP will continue in the next step with a smaller $\theta^{k+1} = \theta^k \cdot \zeta$, where $0 < \zeta < 1$ in order to approach the equilibrium more accurately*.* The iterations continue until θ gets sufficiently small ($\theta < \theta_{min}$)(i.e. users are allowed to change a negligible fraction of their energy schedules).

At step *k* of B-RTP, each user *i* alters her desired/initial energy schedule $\widetilde{x_i}$ into x_i^k, according to her flexibility and the B-RTP's billing. This leads to a total energy cost reduction

$$\Delta C^k = \sum_{t=1}^{T}\left(G\left(\sum_{i=1}^{N}\widetilde{x_i^t}\right) - G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N}\left(x_j^{t,k-1}\right) + x_i^{t,k}\right)\right) \tag{20}$$

Through B-RTP, ESP rewards each user *i* for her contribution to total energy cost reduction, by an energy bill discount

$$\Delta B_i^k = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+\widetilde{x_i^t}\right)-G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N}\left(x_j^{t,k-1,}\right)+x_i^{t,k}\right)\right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+\widetilde{x_i^t}\right)-G\left(\sum_{\substack{j=1 \\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+x_i^{t,k}\right)\right)\right)} \cdot \Delta C^k \tag{21}$$

In Eq. (21), the numerator represents the energy cost reduction that user's *i* behavioral change generated in step *k* of B-RTP. Note that each user acts knowing only what the rest of the users have done in the previous iteration *k-1* of B-RTP and having no knowledge of their actions in the current iteration. The denominator equals to the summation of every user's corresponding contribution and thus we have $\sum_{i=1}^{N}\Delta B_i^k = \Delta C^k$. Therefore, the energy bill discount that each user receives is a fraction of the total energy cost reduction, and equal to her contribution.

In order to combine the volume-aware pricing that RTP proposes and the incentives that B-RTP offers, we designed a hybrid billing mechanism which, in every iteration *k*, calculates the $B_{i,B-RTP}^k$ of each user *i* according to

$$B_{i,B-RTP}^k = \tilde{B}_{i,RTP} - \gamma \cdot \Delta B_i^k - (1-\gamma)\cdot(\tilde{B}_{i,RTP} - B_{i,RTP}^k) \tag{22}$$

Here, $B_{i,RTP}^k$ denotes the energy bill of user *i* in step *k* of the algorithm in case that ESP applies the RTP model (according to Table I). By studying Eq. (22), we observe that for $\gamma = 0$, B-RTP is reduced to the RTP model, while for $\gamma = 1$, the total cost reduction that is derived from the behavioral change of a user is converted into an equivalent reduction in her energy bill. In case $0 < \gamma < 1$, a fraction γ of the cost reduction derived from the behavioral change of a user is converted into discount in her bill and the remaining fraction 1-γ is allocated to all participating users according to RTP. In case that $\gamma > 1$, B-RTP actually penalizes the set of users who are more reluctant to deviate from their desired energy schedule, in order to further favor the flexible users.

By replacing Eqs. (18) and (21) into Eq. (22) for ΔB_i^k and $B_{i,RTP}^k$, respectively, one can easily prove that $\sum_{i=1}^{N} B_{i,B-RTP}^k = G\left(\sum_{i=1}^{N} x_i^{t,k}\right)$, which means that our scheme is budget-balanced and does not generate surplus or deficit of money. B-RTP is summarized in Table II. As researchers in [52] prove, the convergence time of the algorithm of B-RTP is approximately the same for different number of consumers. Moreover, the impact of the number of flexible appliances per user on convergence time is negligible. Finally, the convergence of the following algorithm is proved in [52].

TABLE II. ALGORITHM FOR THE CALCULATION OF ENERGY BILLS AND THE ENERGY CONSUMPTION SCHEDULES IN B-RTP

1	**Initialization**: $k = 0$, $x_i^k = \widetilde{x_i}$, $B_{i,B-RTP}^k = \widetilde{B_{i,RTP}}$, $\forall i \in \mathbf{N}$, $\theta = \theta^0$,θ_{min},ε, ζ
2	**While** $\theta^k > \theta_{min}$ do
3	Calculate G^k
4	$k \rightarrow k+1$
5	**For** each user $i \in \mathbf{N}$
6	Receive B_i^k
7	**Repeat**
8	Update x_i^k
9	$B_{i,B-RTP}^k$ is updated through (17), (18), (21) and (22)
10	Calculate W_i^kusing (14)
11	**Until** reach solution of (15) subject to (1), (7), (12), (19)
12	**End for**
13	Calculate G^{k+1}
14	**If** $G^{k+1} > G^k * (1-\varepsilon)$
15	$\theta^{k+1} = \theta^k * \zeta$
16	**Else**
17	$\theta^{k+1} = \theta^k$
18	**End**

V. Performance Evaluation

In this section, we evaluate our proposed B-RTP scheme using the state-of-the-art RTP scheme as a benchmark. We consider a system consisting of *N* = 10 energy consumers, each of whom operates two curtailable and four shiftable devices. The selection of the 6 categories of devices was done in order to include in the evaluation all possible types of loads. More specifically, each energy consumer may conserve energy through the curtailment of the operation of an A/C and a lighting system, and additionally shift the operation of an oven, a washing machine, a spin dryer and the charging of an EV. Moreover, every user characterizes some of her appliances as non-adjustable loads. In more detail:

- **Lights**: We assume that each household is illuminated by 14 bulbs, which can be either LED (8W), CFL (14W) or incandescent bulbs (60W), and that users want the lights on from 18:00 until 24:00. Thus, user's *i* total desired lighting energy consumption is randomly selected over the interval [0.672 – 5.040 kWh]. We assume that in every time slot, equal energy amounts are consumed.

- **A/C**: Each user operates an A/C system from 14:00 until 22:00. Single A/C units come in different sizes and use from 500 to 1500 watts. User's *i* total desired A/C energy consumption is randomly selected over the interval [4.0-12.0 kWh]. As we did with the lights, we assume that equal energy amounts are consumed in every time slot
- **Oven**: We consider that users classify the oven as a shiftable device. Ovens use 1000 to 5000 watts and are assumed to require at most one hour to complete their task. Therefore, user's *i* total desired oven's energy consumption is randomly selected over the interval [1.0 – 5.0 kWh]. Users' desired oven plug-in times vary from 17:00 to 19:00.
- **Washing Machine**: It falls into the category of shiftable appliances. Washing machines use 400 to 1300 watts and finish their task in less than an hour. User's *i* total desired washing machine energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 09:00 to 12:00.
- **Spin Dryer**: It is also accounted as a shiftable device. The energy use of a spin dryer varies between 1800 and 5000 watts and it takes less than an hour for it to finish its task. User's *i* total desired energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 13:00 to 18:00.
- **EV**: The battery capacity is randomly chosen over the interval [5.5-6 kWh] and the maximum charging rate is 2 kW. Thus, the minimum time that an EV demands in order to be charged is 3 hours. We assume that users desire their EV to start charging somewhere between 00:00 and 05:00 or 18:00 and 21:00, and to finish ideally in 3 hours.
- **Non-adjustable loads**: We assume that users categorize as nonadjustable loads devices, such as the refrigerator, the TV, the freezer, the Wi-Fi Router, etc., which are meant to be ON whenever requested. Thus, users' aggregate energy consumption of critical loads is randomly chosen from [3.6-11.4 kWh] at each timeslot.

The above datasets are derived from [53], [54], [55] and are summarized in Table III. The aggregate desired ECC is presented in Fig. 3. The scheduling horizon consists of *T* = 24 time slots of hourly duration. For the stepsize, we set $\theta^0 = 0.95$, $\zeta = 0.50$, $\varepsilon = 0.001$ and $\theta_{min} = 0.01$ throughout the simulations. Regarding the parameters of energy cost function in Eq. (13), b and c are usually set to 0, while the value of parameter a varies from 10^{-4} to 0.05 in [11], [14], [26], [31] and [51]. In this work, parameters b and c are also set 0, while a is chosen to be 0.01, 0.02 or 0.03, which is the usual case in the aforementioned works also. Moreover, in [56] parameter δ of Eq. (8) is set to 1 implying perfectly flexible energy consumers. In this paper, in order to evaluate B-RTP in scenarios of various flexibility classes of end users, δ varies from 1 to 1.5. For the same reason, we choose ω of Eq. (4) to vary from 0.1 to 6.

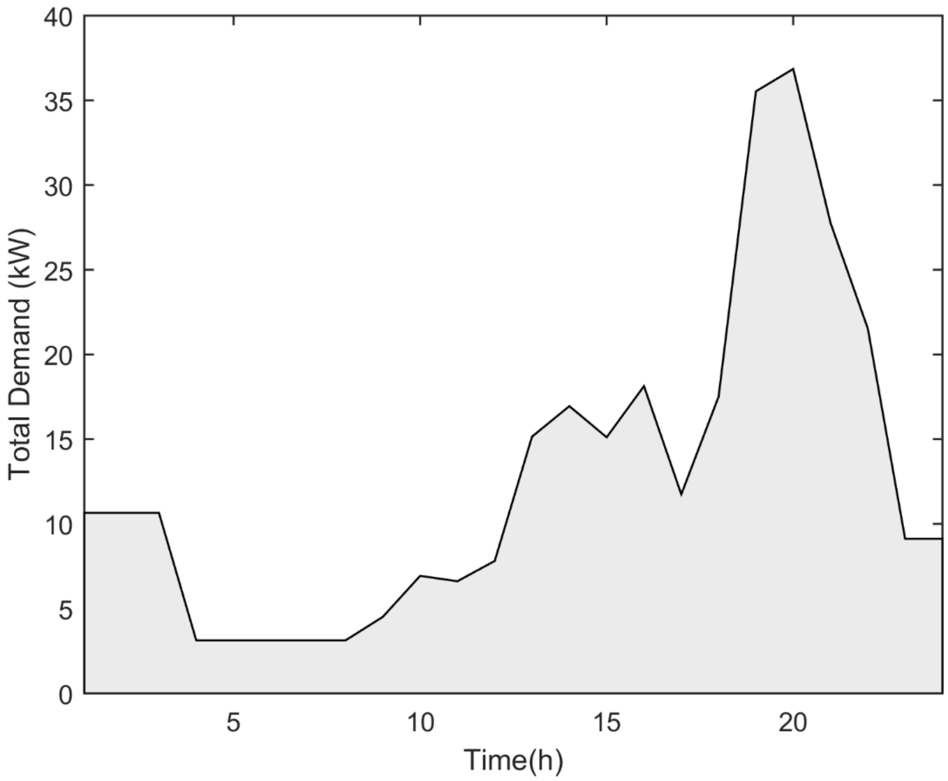

Figure 3: Aggregate daily users' Energy Consumption Curve

TABLE III. ELECTRICITY CONSUMPTION OF HOUSEHOLDS' APPLIANCES

Appliance	**Power (kW)**	**Type of device**	$\widetilde{t_{i,d}^{a}}$	**Duration (h)**	$\widetilde{t_{i,d}^{b}}$	**Energy (kwh)**
-	-	Non-adjustable	00:00	24	24:00	[3.6-11.4]
Lighting	[0.008-0.060]	Curtailable	18:00	6	24:00	[1.2-5.0]
A/C	[0.5-1.5]	Curtailable	14:00	8	22:00	[4.0-12.0]
Oven	[1.0-5.0]	Shiftable	[17:00-19:00]	1	[17:00-19:00]	[1.0-5.0]
Washing Machine	[0.4-1.3]	Shiftable	[10:00-13:00]	1	[10:00-13:00]	[0.4-1.3]
Spin Dryer	[1.8-5.0]	Shiftable	[14:00-19:00]	1	[14:00-19:00]	[1.8-5.0]
EV	[0.0-2.0]	Shiftable	[00:00-05:00,18:00-21:00]	3	[03:00-08:00,21:00-24:00]	[5.5-6.0]

In order to demonstrate the performance of the B-RTP model for different classes of energy consumers – ESP customers, we consider three use cases:

a) <u>Low Flexibility</u>: Energy consumers are reluctant to change their energy consumption habits. Parameter $\delta_{i,d}$ for each user $i \in \boldsymbol{N}$ and $d \in \boldsymbol{D}_{s,i}$ is randomly selected over

[1.20-1.50], while parameter ω_i is randomly chosen over [3,6]. Finally, in this use case, we consider users that set relatively strict deadlines, i.e. they allow their EMSs to schedule their shiftable loads not more than one to two hours after $\widetilde{t_{i,d}^{b}}$.

b) Medium Flexibility: Energy consumers are more price-sensitive than in the 'Low Flexibility' use case. Parameter $\delta_{i,d}$ is randomly selected over [1.10,1.20] $\forall\, i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}}$. Parameter ω_i is randomly chosen over [1.0,3.0]. Users set their deadlines two to four hours after their $\widetilde{t_{i,d}^{b}}$.

c) High Flexibility: In this use case, energy consumers are most willing to participate in DSM programs, even for a relatively small repayment. Parameter $\delta_{i,d}$ is randomly selected over [1.00,1.10] $\forall\, i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}}$. Parameter ω_i is randomly chosen over [0.1,0.5]. Users set their deadlines two to six hours after their $\widetilde{t_{i,d}^{b}}$.

Without loss of generality, in all of the above cases, parameter U_{max} in the utility function for curtailable loads is set to 0. Moreover, $\underline{x_{i,d}^{t}}$ is set to 0 $\forall i \in \boldsymbol{N}, d \in \boldsymbol{D_{c,i}}$. In order to assess the performance of B-RTP algorithm, the following Key Performance Indicators (KPIs) are used:

- Energy Cost (*G)*, as defined in Eq. (13), 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, that is, how successful it is in incentivizing customers to adopt energy-efficient habits.
- Aggregate Users' Welfare (*AUW)* is a KPI that expresses the competitiveness of an ESP that adopts a billing strategy in an open electricity market:

$$AUW = \sum_{i=1}^{N}\left(\sum_{d=1}^{D_{c,i}}\sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}}\sum_{t=1}^{T} DU_{i,d}^{t}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right) - B_{i,RTP}\right) \quad (23)$$

- Fairness (F_i) is a KPI that indicates the fraction of user's *i* contribution to system cost reduction that she will be rewarded in terms of energy bill discount:

$$F_i = \frac{D_i^R}{D_i^A}, \forall i \in \boldsymbol{N}, \quad (24)$$

where,

$$D_i^R = \frac{\widetilde{B_{i,RTP}} - B_i}{\sum_{i=1}^{N}\left(\widetilde{B_{i,RTP}} - B_i\right)}, \forall i \in \boldsymbol{N} \quad (25)$$

represents the discount that user *i* receives in her energy bill as a portion of the total discount in all users' bills, and

$$D_i^A = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1 \\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)\right)} \quad (26)$$

represents the discount achieved by user *i*, i.e. her contribution to system cost reduction, as a fraction of the summation of all users' corresponding contributions. This is calculated employing the concept of Shapley value from cooperative Game Theory [57]. In this regard, user's impact in the reduction of system cost is measured through the comparison of the total energy cost in: 1) the case in which user *i* performs the alterations in her ECC, 2) the case in which user *i* follows her desired ECC. Values of F_i close to 1 indicate a fairer correlation between the behavioral change of user *i* and the reward that she gets for it.

The adaptability of the Hybrid B-RTP(*γ*) scheme gives ESP the opportunity to select its own strategy with respect to users' reward, by adjusting properly the value of *γ*. According to the price elasticity of its customers and the DR services it has to provide to the various smart grid market stakeholders, ESP will select a certain value of γ in order to achieve an attractive trade-off among the above KPIs.

A. Low Flexibility Use Case

In the Low Flexibility case, ESP needs to provide its customers with more generous financial incentives in order to motivate them towards more energy-efficient ECCs, as they are not so price-sensitive. Fig. 4 depicts the ratio between the energy cost G (across the whole time horizon) with hybrid B-RTP and the energy cost G with RTP as a function of *γ*. The graphs in Fig. 4, represent the cases of energy with low generation cots (*c* = 0.01), medium-cost energy (*c* = 0.02) and high-cost energy (*c* = 0.03). We notice that even in the low flexibility use case, B-RTP is able to bring a cost reduction of 10% in comparison with RTP (for *γ*=2), in case of low- and medium-cost energy (*c*=0.01, *c*=0.02) and 13% in case of high-cost energy (c = 0.03). As cost of energy rises, it is reasonable for *G* to further decline, since the energy bills are higher and thus customers are more willing to exploit their schedulable loads.

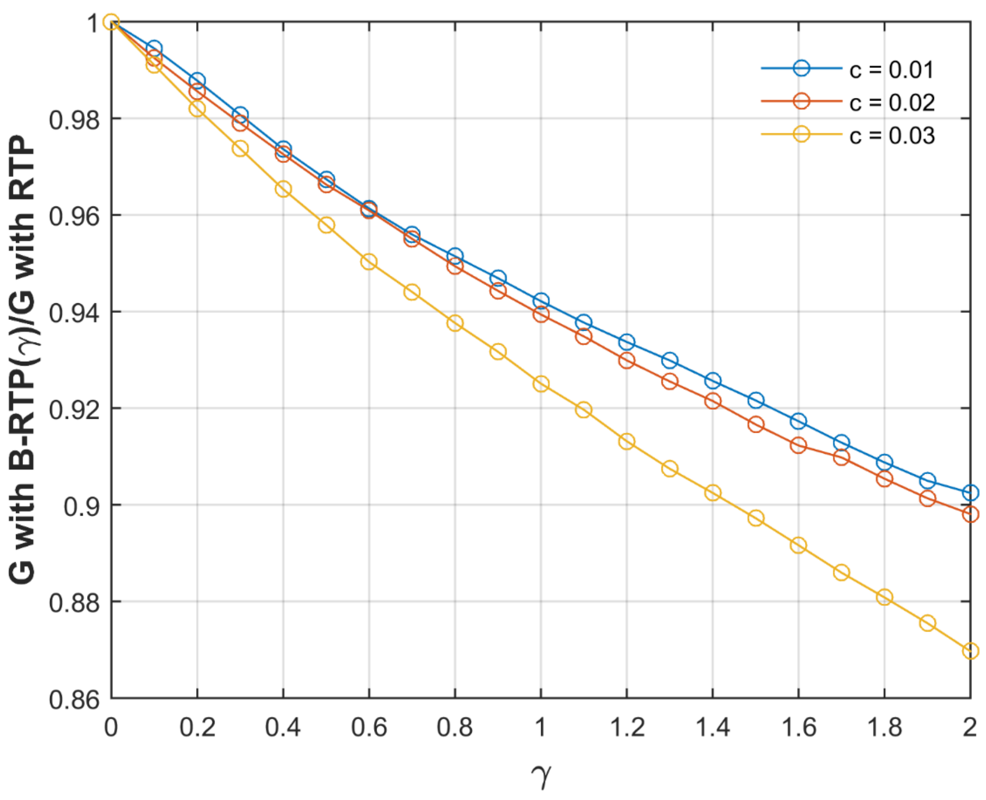

Figure 4: Ratio between *G* with B-RTP(*γ>0*) and *G* with RTP (γ=0) as a function of *γ* in Low Flexibility use case

These results are expected for γ = 2, which could correspond to a case, for example, of an imminent congestion event in a certain area. As it is inferred from Eq. (22), values of γ greater than 1 imply that ESP over-rewards the more flexible users for their DSM actions, while it imposes a monetary penalty to the less flexible ones. Fig. 5 presents the ratio between *AUW* with B-RTP and *AUW* with RTP scheme as a function of γ. According to it, the aforementioned energy cost reduction does not come with any significant users' welfare decrease even in the low flexibility use case. In fact, ESP could select γ to be up to 1.8 and *AUW* would not be lower than that under RTP scheme. This is explained firstly by the fact that a load shift or a load cut, which are the reasons of the decrease of a users' comfort, are higher compensated by the ESP, when $\gamma > 1$. Moreover, even the more flexible users in this inelastic set of energy consumers manage a relatively small cost reduction ΔC. Thus, the penalties in the energy bills of the less energy efficient users are too small compared to their RTP bills to justify a large decrease in *AUW*. In other words, given that ESP's customers are a set of inelastic users, increasing γ diminishes *AUW* by a slow rate. Hence, B-RTP (comparing to RTP), manages to reduce energy costs by 9-12%, depending on conventional energy generation cost level (c), without sacrificing at all the aggregate users' welfare. ESP could continue increasing γ in order to further motivate users to shift or shed their loads and therefore achieve even higher energy cost reduction. However, this would be done at the expense of users' welfare. Finally, we note in Fig. 5 that *AUW* reaches its peak for γ = 0.8 independently of the value of c. Apparently, in case of high-cost energy (c = 0.03), the gap between *AUW* under B-RTP and *AUW* under RTP is larger, since the financial motivation for the users is larger. This leads them to more energy efficient actions (load shifts and cuts) and hence lower energy bills and finally higher AUW. In other words, the bill discounts are greater than their marginal utility, which they sacrifice to get them.

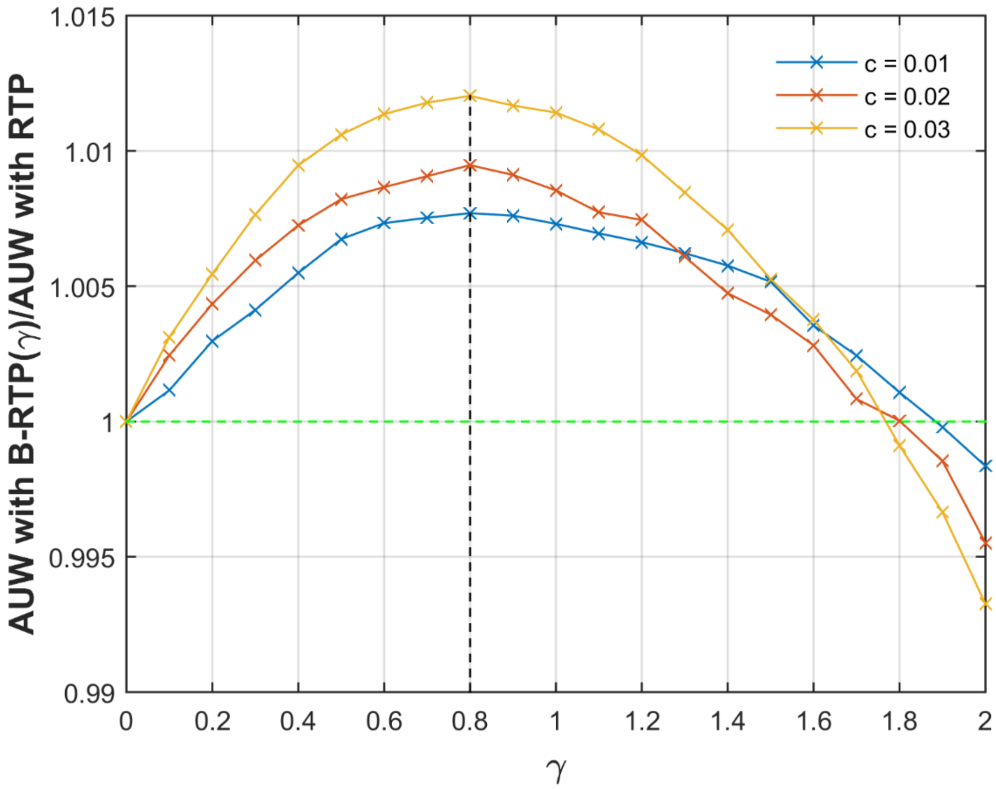

Figure 5: Ratio between *AUW* with B-RTP(γ>0) and *AUW* with RTP (γ=0) as a function of γ in Low Flexibility use case

In order to examine the impact of γ on users' welfare in more detail, we depict in Fig. 6 the ratio between users' welfare in case of $\gamma \in [0\,,0.8\,,1,1.5]$ and in case of RTP for every user $i \in \boldsymbol{N}$ and c = 0.02. Ten users are sorted based on their flexibility, with i=1 denoting the more flexible user and i=10 the less flexible one[2]. Studying Fig. 6, we observe that, as we expected, W_i of the less price inelastic users i increases with γ. On the other hand, RTP is in the best interest of price inelastic users, since not being willing to change their energy consumption patterns, it provides them with financial benefits that others created. As in Fig. 5, in Table IV we establish the preference of users for B-RTP(γ=0,8) on average. Also, we note that in B-RTP(γ=1,5), even if price inelastic users are penalized in order for the flexible users to receive a generous bonus for their behavioral change, users' welfare is marginally higher on average than in RTP in this low flexibility use case.

[2] Flexibility is a function of parameters ω and δ, used in Eqs. (4) and (8), respectively, and also $\widetilde{t_{i,d}^{a}}$, $\widetilde{t_{i,d}^{b}}$, $t_{i,d}^{l}$ (i.e. users' desired ECC). Thus, sorting users based on their flexibility is not a straightforward task and has been done approximately. This is why there is not a continuity in the variation of users' welfare for a certain value of γ. This is also observed in corresponding graphs for the other use cases.

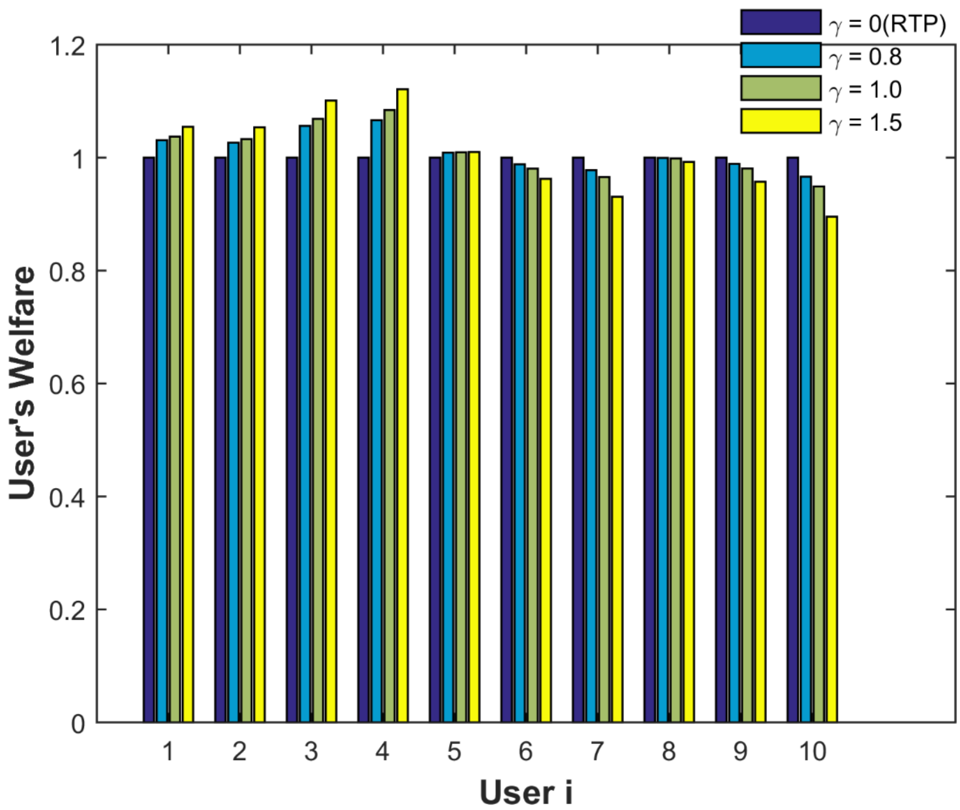

Figure 6: Ratio between users' welfare for various values of γ and users' welfare for γ = 0 (RTP) in Low Flexibility use case

TABLE IV RATIO BETWEEN AVERAGE USERS' WELFARE FOR DIFFERENT VALUES OF γ AND AVERAGE USERS' WELFARE FOR γ=0 (RTP) IN LOW FLEXIBILITY USE CASE

γ	0 (RTP)	0.8	1.0	1.5
$\overline{UW}(B-RTP(\gamma))/\overline{UW}(RTP)$	1	1.0094	1.0085	1.0039

Fig. 7 depicts the Cumulative Distribution Function (CDF) of F_i for different values of γ. Cost parameter c is set to 0.02. As analyzed above, F_i is an index of how fairly the energy cost reduction is allocated to users. The fairest way of distributing energy savings among the users is represented by $F_i = 1$. Fig. 7 shows that B-RTP (γ=1) is the fairest billing mechanism. This was expected as it incentivizes users towards an energy-efficient behavior so that they receive a generous discount in their bills. Under RTP (γ = 0), inflexible users benefit from the others' actions and thus are not motivated to change their energy consumption behavior, while demand responsive customers see their actions not being sufficiently compensated. This discourages users to deviate from their desired ECC. For gradually increasing γ the distribution of users around $F_i = 1$ gets narrower (i.e. fairer billing) and for γ=0.8 (which maximizes *AUW*), it is much closer to $F_i = 1$. For values of γ greater than 1, the distribution of users around $F_i = 1$ starts getting wider again as we can see in case of γ = 1.5. Still, the mean value of F_i (Table V) is closer to 1 than RTP, meaning that B-RTP(γ=1.5) is a fairer billing scheme than RTP on average. If ESP chooses to impose the fairest possible pricing scheme, B-RTP will manage a cost reduction of 6-7.5% comparing to RTP and a slightly higher *AUW*.

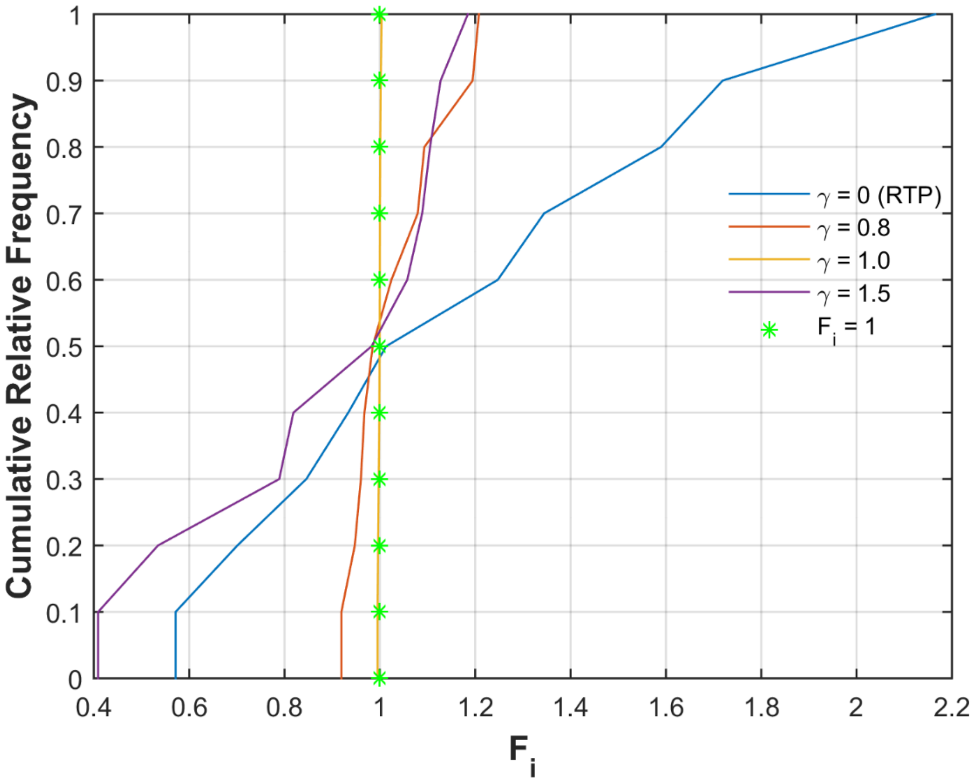

Figure 7: CDF of F_i among participating users under B-RTP for various values of γ in Low Flexibility use case

TABLE V MEAN VALUES OF F_i FOR DIFFERENT VALUES OF γ IN LOW FLEXIBILITY USE CASE

$\boldsymbol{\gamma}$	0 (RTP)	0,8	1	1,5
$\overline{\boldsymbol{F}}$	1.2131	1.0379	1	0.9097

B. <u>Medium Flexibility Use Case</u>

In the medium flexibility use case, the concept of Figures 8, 9, 10, 11 is similar to that of Figures 4, 5, 6, 7, respectively, of the previous low flexibility use case. In this use case, several of the ESP clients represent energy consumers with DR capability. They are more price-sensitive than in the former case but still not eager to change their energy behavior without a significant financial reimbursement. Thus, in Fig. 8, we observe that B-RTP achieves a larger energy cost reduction comparing to RTP scheme. Similarly to the low flexibility use case, as γ increases the cost reduction declines in almost linear fashion. However, for $\gamma > 1.3$, this happens at the expense of *AUW* (Fig. 9), which declines as the less flexible users are penalized so that the more flexible ones achieve a quite generous bonus. In this use case, users seem to be less tolerant to the increase of γ above 1. This is because users, being more price elastic comparing to the low flexibility use case, create a larger cost reduction, which translates into stricter penalties for the less DR-active users. Nevertheless, in case of c = 0.02, B-RTP reduces energy cost by up to 16% compared to RTP without sacrificing AUW ($\gamma = 1{,}3$). In case of higher or lower cost of energy, this cost reduction is larger (21%) or smaller (11%) respectively. Here, we observe a larger gap between the 3 plots of Fig. 8 when we compare them with those of Fig. 4, since users are more price-responsive and higher energy costs lead them to even more load shifts and cuts in order for them to benefit from B-RTP.

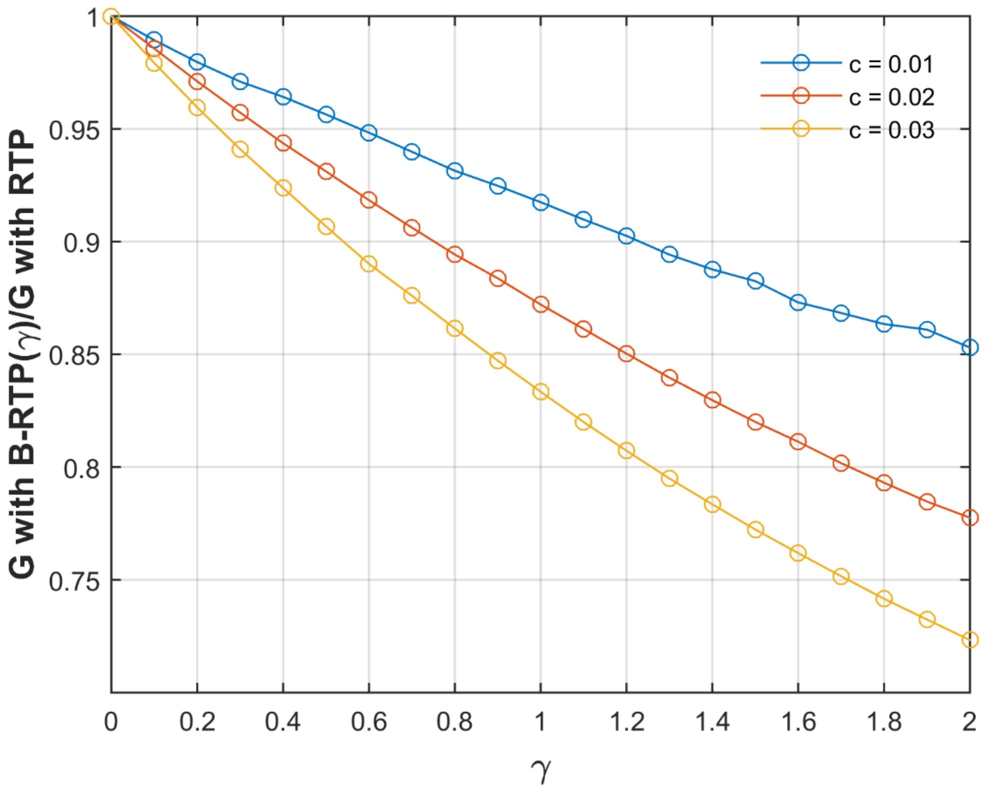

Figure 8: Ratio between *G* with B-RTP(γ>0) and *G* with RTP (γ=0) as a function of *γ* in Medium Flexibility use case

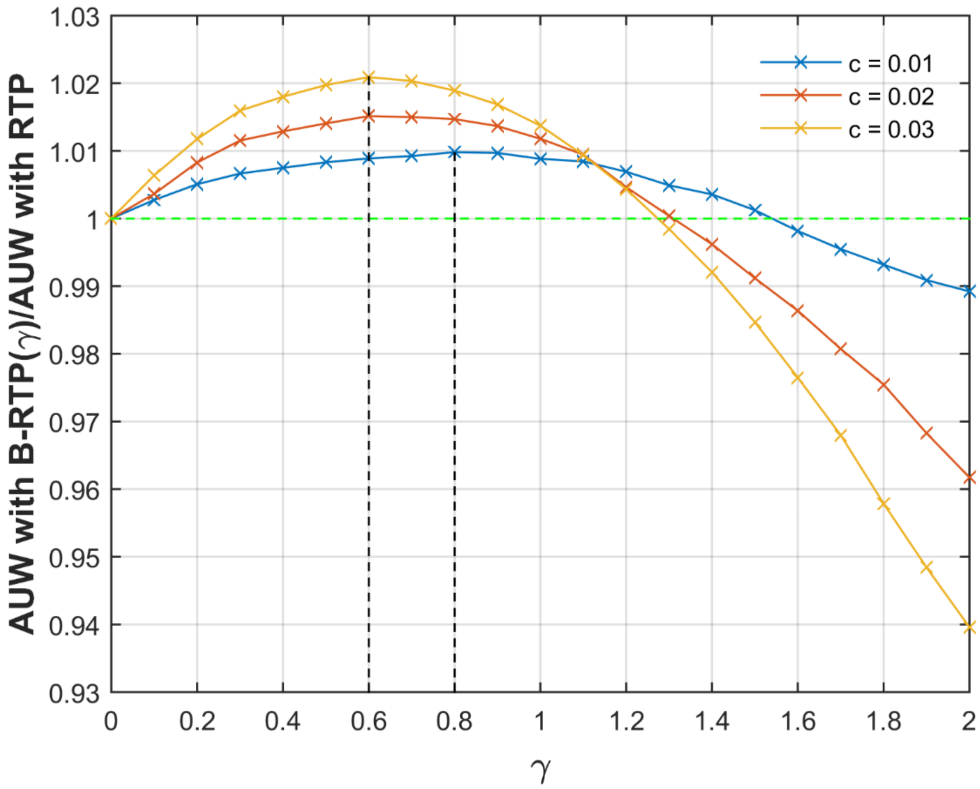

Figure 9: Ratio between *AUW* with B-RTP(γ>0) and G with RTP (γ=0) as a function of γ in Medium Flexibility use case

In Fig. 10 and Table VI, we can see that, as in the low flexibility use case, increasing γ benefits the more price elastic users, who take advantage of the billing mechanism and receive a high discount in their energy bills. On the other hand, the rest of the users experience a steeper downfall in their Welfare as γ increases compared to the previous use case. This can be interpreted, not only by the higher penalties these users have to pay, but also by the fact that they are not totally price inelastic energy consumers as in the low flexibility use case.

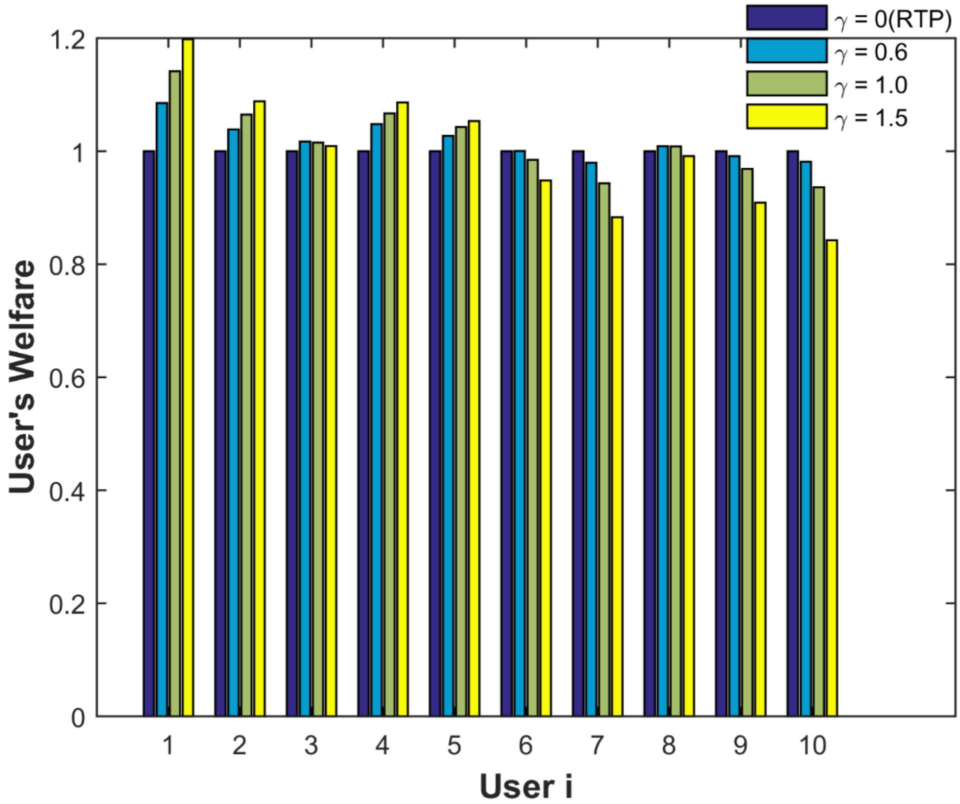

Figure 10: Ratio between users' welfare for various values of γ and users' welfare for γ = 0 (RTP) in Medium Flexibility use case

TABLE VI RATIO BETWEEN AVERAGE USERS' WELFARE FOR DIFFERENT VALUES OF γ AND AVERAGE USERS' WELFARE FOR γ=0 (RTP) IN MEDIUM FLEXIBILITY USE CASE

γ	0 (RTP)	0,6	1,0	1,5
$\overline{UW}(\mathbf{B-RTP(\gamma)})/\overline{UW}(RTP)$	1	1.0149	1.0117	0.9911

As in the low flexibility use case, we see in Fig. 11 and Table VII that B-RTP (γ=1) is the fairest billing mechanism, while RTP is the least fair among B-RTP schemes with parameter $0 \leq \gamma \leq 1$. Even B-RTP (γ=1.5) compensates in a fairer way more users than RTP does. So, ESP can choose *γ*=1 to efficiently incentivize its customers to alter their ECCs and achieve a cost reduction of 6.5, 12.5 or 17% over RTP, depending on energy generation cost parameter *c*. Alternatively, ESP could choose *γ*=0.6 to maximize *AUW* in cases of medium-cost and high-cost energy and achieve a 7.5 and 11%larger cost reduction than RTP respectively in a fairer manner. In case of low-cost energy (*c* = 0.01), ESP in order to maximize *AUW* should select *γ* = 0.8 which results in a 5% cost reduction over RTP.

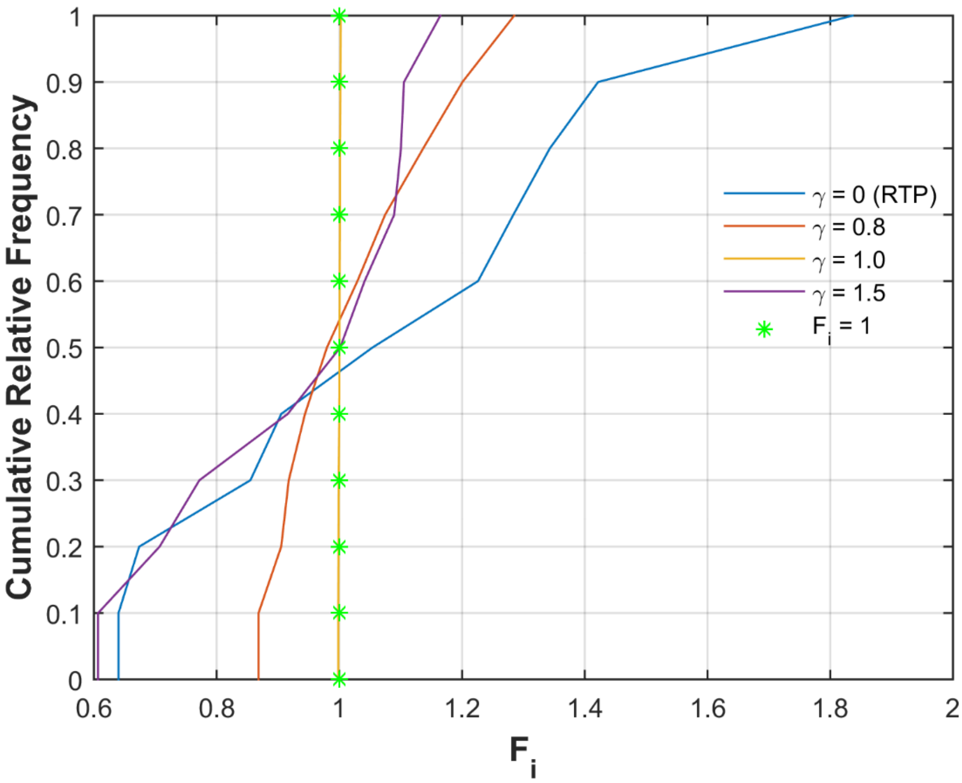

Figure 11: CDF of F_i among participating users under B-RTP for various values of γ in Medium Flexibility use case

TABLE VII MEAN VALUES OF F_i FOR DIFFERENT VALUES OF γ IN MEDIUM FLEXIBILITY USE CASE

γ	0 (RTP)	0,6	1	1,5
$\overline{F}$	1.1239	1.0341	1	0.9504

C. High Flexibility Use Case

In this subsection, we examine the case when ESP's customers are a set of highly price-sensitive users, who are eager to exploit their schedulable loads in order to gain discounts in their energy bills. In this high flexibility use case, Figures 12, 13, 14, 15 are once again similar to their corresponding Figures 4, 5, 6, 7 of the low flexibility use case. Thus, Fig. 12 illustrates a downturn in energy cost comparing to RTP scheme. However, increasing γ diminishes *AUW* in much steeper fashion in comparison to the two former use cases (Fig. 13). This is because B-RTP (γ>1) will penalize users who are much more willing to provide flexibility services in order for them to get financially rewarded and not users who are price-inelastic. This result is very interesting from the ESP's business perspective in case it participates in various types of flexibility markets, where DSM units can be sold in really competitive prices (e.g. to solve an imminent congestion problem). In the latter case, users would be more tolerant to a fine imposed to their energy bills. This is illustrated in Fig. 14 and Table VIII (c = 0.02), in which it is clear that the welfare of less flexible users decreases for γ=1.5. Conclusively, B-RTP reduces energy cost by 16 % over RTP when c = 0.01, by 24% when c = 0.02 and even by 27% when c = 0.03, while simultaneously managing to keep *AUW* above that of RTP. In case of B-RTP(γ=0,5) which maximizes *AUW* for c = 0.02 or c = 0.03, the energy cost reduction reaches

14% and 17%, respectively. In case of low-cost energy (c = 0.01) *AUW* is maximized for γ = 0.6 and the equivalent cost reduction is 10.5% in comparison with RTP.

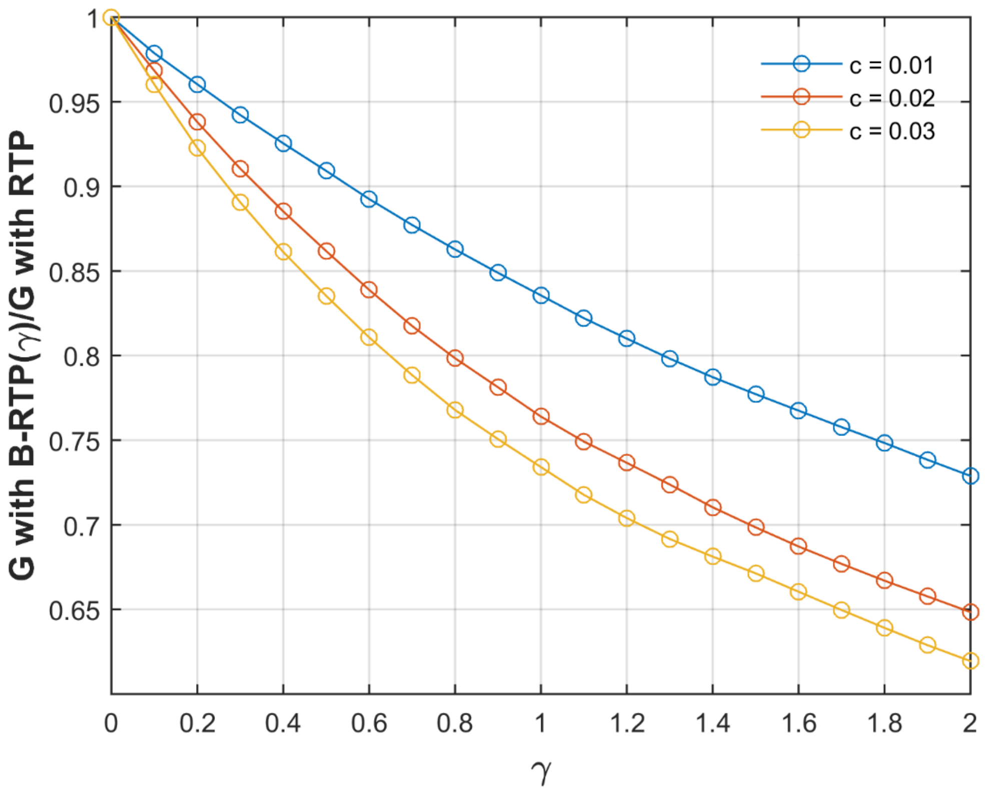

Figure 12: Ratio between *G* with B-RTP(γ>0) and *G* with RTP (γ=0) as a function of γ in High Flexibility use case

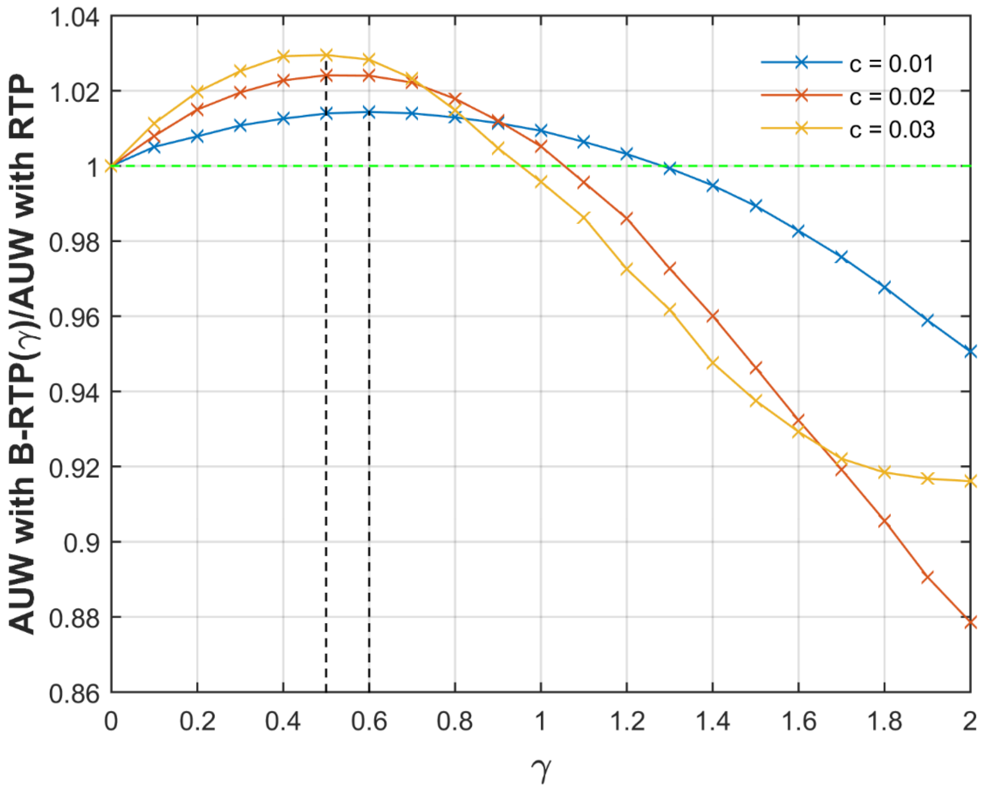

Figure 13: Ratio between *AUW* with B-RTP(γ>0) and *AUW* with RTP (γ=0) as a function of γ in High Flexibility use case

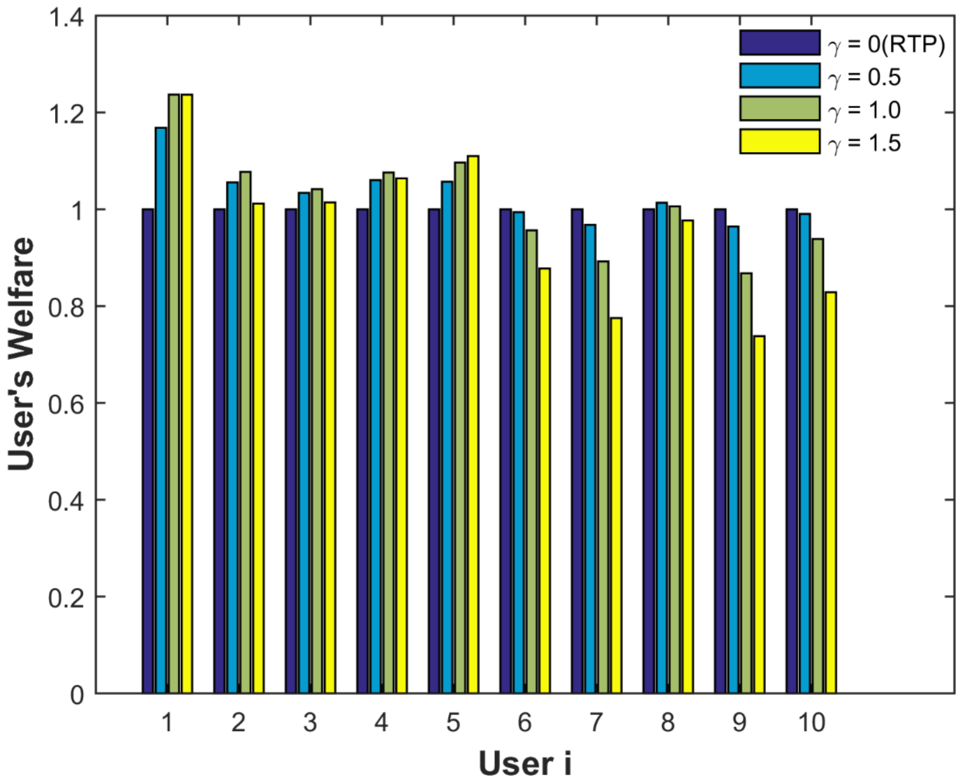

Figure 14: Ratio between users' welfare for various values of γ and users' welfare for γ=0 (RTP) in High Flexibility use case

TABLE VIII RATIO BETWEEN AVERAGE USERS' WELFARE FOR DIFFERENT VALUES OF γ AND AVERAGE USERS' WELFARE FOR γ=0 (RTP) IN HIGH FLEXIBILITY USE CASE

$\boldsymbol{\gamma}$	0 (RTP)	0,5	1,0	1,5
$\overline{\boldsymbol{UW}}(\mathbf{B}-\mathbf{RTP}(\boldsymbol{\gamma})) \Big/ \overline{\boldsymbol{UW}}(\boldsymbol{RTP})$	1	1.0236	1.0052	0.9432

In the CDF of F_i (Fig. 15), we re-establish that B-RTP(γ=1) is the fairest billing mechanism, while RTP the least fair one. By gradually increasing γ and as it approaches 1, the distribution of users gets narrower (fairer pricing), until γ surpasses 1 and the users' distribution starts widening again. We also notice that even B-RTP with γ=1.5 allocates the energy cost reduction to the users in a fairer way than RTP (Table IX). In more detail, B-RTP with γ=1.5 overcharges some users for their energy consumption, although it charges users more fairly and thus it is a stronger motivator towards energy-efficient ECCs than RTP. This policy would bring a large cost reduction (e.g. 30% for c = 0.02) although it would decrease *AUW* (e.g. 6% for c = 0.02). This policy could be selected in the case of emergency situations (e.g. congestion issues in a specific network location, governmental policies to cope with energy poverty issues, etc.), when energy cost is requested to severely decrease at any cost.

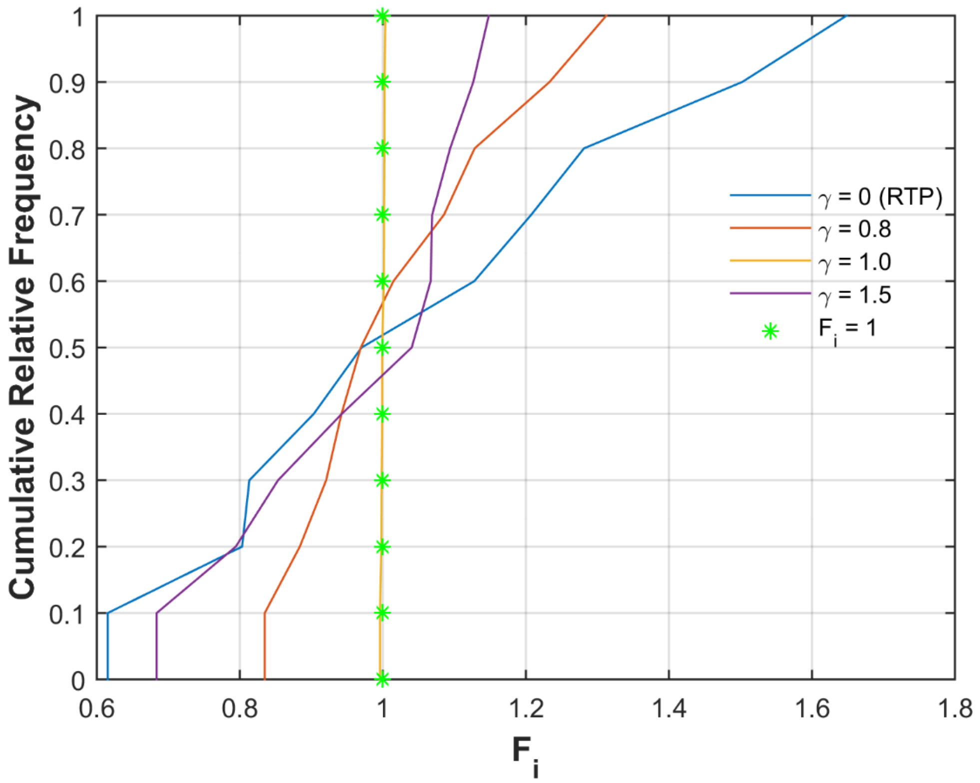

Figure 15: CDF of F_i among participating users under B-RTP for various values of γ In High Flexibility use case

TABLE IX MEAN VALUES OF F_i FOR DIFFERENT VALUES OF γ IN HIGH FLEXIBILITY USE CASE

γ	0 (RTP)	0.5	1	1.5
$\overline{F}$	1.0873	1.0325	1	0.9819

In the 3 use cases examined above, we demonstrated that B-RTP offers a much more attractive trade-off between widely accepted KPIs than the RTP scheme for all levels of energy generation cost and all levels of the end users' elasticity. Based on these results, we consider B-RTP a very useful tool in the hands of an ESP, which can exploit it in order to participate in several types of flexibility markets (i.e. balancing, congestion management, voltage control, frequency control, N-1 adequacy) with efficient DSM services, while being fair towards its customers and without sacrificing the level of eligibility of its services in an open and competitive retail market. In emergency circumstances, where the stability of the system is at risk and the energy cost is about to increase dramatically (e.g. congestion market), an ESP making use of B-RTP, can carry through the task with a relatively smooth reduction of users' welfare.

VI. Conclusion

In this paper, we focused on modern energy pricing models and argued that they do not fairly reward demand responsive users, who are more willing than others to adopt energy-efficient habits. Thus, existing pricing models are not designed to trigger behavioral changes as they do not provide energy consumers with attractive incentives in the form of fair compensation. Motivated by this observation, we developed a hybrid billing mechanism, namely Behavioral Real Time Pricing. B-RTP disposes an adjustable level of rewarding users by offering them financial incentives to modify their ECCs. B-RTP can be a valuable tool in the hands of an ESP in order for the latter to employ innovative business models and respective revenue streams mainly by selling DSM units in various types of flexibility markets. It aims at motivating its customers to exploit their shiftable and curtailable devices in order to reduce the cost of conventional energy usage. Our evaluation uses a non-profit version of RTP as a benchmark and we show that B-RTP manages to prompt energy behavioral changes of users much more efficiently than RTP does. We assume in this work that the desired ECC is a priori known. In our future work, we will advance the model of B-RTP in order to take into account use cases, where the desired ECC is unknown. Finally, we plan to study the impact of the B-RTP in: islanded microgrids, energy communities and innovative business models for ESPs towards the latters' participation in the emerging flexibility markets.

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