Development of Real Time Energy Pricing Schemes that Incentivize Behavioral Changes

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***Abstract*— Modern energy markets, smart grids and high penetration of Renewable Energy Sources (RES) necessitate the development of modern pricing schemes. Energy Service Providers (ESPs) and end users (consumers) will mutually benefit from the cost reduction and the stability improvement that behavioral changes in the energy consumption can bring. Modern pricing schemes should be able to trigger these behavioral changes. As we argue in this paper, the energy pricing schemes proposed so far (e.g. Real Time Pricing) do not reward the users (energy consumers) that modify their behavior, and are therefore unfair and unable to trigger behavioral changes. Based on this research motivation, we develop a Behavioral Real Time Pricing (B-RTP) scheme, which offers an adjustable level of financial incentives to participating users, rewarding desirable behavioral changes (in the form of their Energy Consumption Curve). Our evaluation results compare RTP and B-RTP, showing that our proposed B-RTP affects the behavior of the participating users much more efficiently than RTP, outperforming the latter in all widely adopted metrics. B-RTP is able to reduce energy consumption by up to 20% compared to RTP without sacrificing users' welfare and ESP profits.**

Keywords—smart grids; real time pricing; incentives, behavioral change

I. Introduction

Three major developments are currently in progress in electricity markets. The first is the residential users' participation in electricity markets through Demand Side Management (DSM), which highly increases the importance of the tradeoff between the quality of service (QoS) offered by an Service Provider and its profit margins. The second is the high penetration of Renewable Energy Sources (RES) in the electricity generation mix, which results in high levels of variance in the energy production rate. This creates the need to modify the Energy Consumption Curves (ECCs) of participating users in order to exploit available energy more efficiently and better align supply and demand. Thirdly, Energy Storage Systems (ESSs) are available to mitigate the aforementioned variability and increase the stability of the system. However, their cost is not negligible and there is a need to minimize investment expenses. Therefore, the development of advanced pricing schemes, able to exploit these three developments and deliver more efficient energy services, is of great importance.

In particular, collective DSM participation can be undertaken by an independent market entity, to which we refer as Electricity Service Provider (ESP). In this paper, we assume that each user participates in the market through an a priori determined ESP on a contractual basis [12], i.e., the ESP-user interaction is modeled as a regulated monopolistic market. This use case represents the cases where: 1) the profit margins of the ESP company are regulated, 2) users form a cooperative organization to represent their interests, and 3) the aggregating company is a public (regulated) organization. Throughout this paper, we will refer to the aggregating entity with the generic term (ESP) and cover all three use cases.

Historically, the energy pricing models started with traditional flat electricity tariffs. In the flat pricing scheme, each consumer is charged with an identical and time invariant price per energy unit. The first pricing scheme that tried to interact with the end users' behavior was Inclining Block Rates (IBR). In IBR, the higher the total energy that an end user consumes, the higher is the price per energy unit. The objective of IBR scheme is to create a barrier on the overuse of energy and thus prevent an energy shortage and/or network failures. The next step was Time-Of-Use (ToU) pricing, where prices are set a priori and independently of the end users total consumption, but are different for each time of the day. In this way, ToU incentivizes users, apart from curtailing their demand, to also shift their demand from peak to off-peak hours or to hours with higher RES production. Finally, Real-Time Pricing (RTP) is based on a similar rationale with ToU, but calculates prices in almost real time. In RTP, prices are analogous to the dynamic ratio between the total energy production cost (i.e. supply) and the total amount of consumption (i.e. demand).

A pricing scheme has to achieve an attractive trade-off among the following requirements (KPIs): i) the end user's satisfaction, ii) the stability of the energy production/ transmission/consumption system, and iii) the financial profitability of the company that offers energy services according to this scheme. The first requirement is also referred to as *user's welfare* and is formulated as the difference between a utility function that expresses how much an end user values a specific consumption pattern and the cost of energy that s/he consumes. Several studies regard this KPI as their system's objective, e.g. [1], [2], [3], [4]. The second requirement is also

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denoted as *behavioral efficiency* and expresses the capability of a pricing scheme to achieve the objectives that motivated it in the first place (e.g. load curtailments and shifts). Intuitively, behavioral efficiency of a pricing scheme expresses how friendly it is to a TSO/DSO (addressing issues related to energy network stability, efficiency and costs) and implicitly affects several financial metrics (e.g. investments in RES, energy storage and network upgrades). Usually, it is linked with minimizing the system's energy cost, as in [5], [6], [7], [8]. The third requirement is also referred to as *profit dynamics* and represents the profit percentage per energy unit and the total revenues of the Energy Service Provider (ESP). In other words, it expresses the financial growth potential of the service provider that exploits a specific pricing scheme. Relatively few studies account for the third requirement; see e.g. [9], [10].

Beyond these objective requirements, the pricing algorithm has to adapt to the use case for which it is designed to be used. There are two major (types of) use cases appearing in commercial scenarios: the first considers an a priori known voluntary user's ECC and the second an unknown ECC. By voluntary, we mean the natural (unforced) consumption behavior of a user, in the absence of time varying penalties or rewards.

The first use case applies in fully automated houses, where users automatically/electronically control their electric devices by setting their preferences online. Intelligent energy management algorithms control the operation of devices according to their users' preferences, which express their own tradeoff between cost and comfort. In this use case, there are two subcases, load curtailments and load shifts, where the energy management algorithm reduces or shifts user load according to the user's preferences. In the second use case, the user's desired (voluntary) energy consumption is unknown. This relates to less automated houses, in which ESPs are only able to monitor users' current ECC. In this work, we focus on the first use case and more specifically, with the first sub case of load curtailment and leave the other case as future work.

Motivated from the current situation in the electricity market and the lack of a pricing scheme able to incentivize end-users efficiently, we propose: i) a novel pricing scheme referred to as Behavioral - Real Time Pricing (B-RTP), which quantifies the cost reduction that each end user's load curtailment introduces to the system and rewards him according to it, ii) a mechanism that is able to adjust the degree of incentives and thus indirectly control the aggregated energy consumption, iii) a holistic comparison between the proposed B-RTP and a baseline version of an existing RTP scheme that is widely adopted in the literature (benchmark).The remainder of the paper is organized as follows: Section II analyzes our system model, describes the existing RTP model and introduces the proposed B-RTP scheme. Section III evaluates the proposed pricing strategy and compares it to RTP. Finally, Section IV concludes and gives some directions for future work.

II. System Model and Proposed B-RTP Algorithm

In the first subsection, we describe the concept of RTP, while in the second, we introduce and analyze in detail our proposed pricing scheme. Finally, in the third subsection, we describe the energy consumer model that we use and present the realization scheme of B-RTP.

A. Real Time Pricing (RTP)

We start by analyzing the RTP scheme ([11]), which we will later extend to the proposed Behavioral RTP (B-RTP). We consider a system consisting of an ESP and the set $\boldsymbol{N}=\{1,2,..,N\}$ of its clients/energy consumers. Without harm of generality, ESP provides its clients with electricity, in order to cover their demand. In order to do so, ESP participates in wholesale energy markets and purchases the required amount of energy at a cost that is time-variant and is a function of the aggregated consumption of all N end users. We consider a discrete-time model with a finite horizon to model a day. Each day is divided into a set $\boldsymbol{H}=\{1,2,..,T\}$ timeslots of equal duration. The energy that user $i \in \boldsymbol{N}$ consumes at time interval $k \in \boldsymbol{H}$ is denoted as x_i^k. In the literature, in order to evaluate pricing models, an increasing convex function G is adopted (e.g. [10], [11], [16]) to (approximately) model the cost of energy that comes from conventional generation. Function G is often assumed quadratic, in which case the energy generation cost at timeslot k is:

$$G^k = G(\textstyle\sum_{i=1}^{N} x_i^t) = c \cdot (\sum_{i=1}^{N} x_i^t)^2 , \qquad (1)$$

where c is an appropriate parameter.

In the monopolistic market that we assume, the ESP uses the average energy cost to calculate the electricity prices. Specifically, in the RTP scheme, the price ρ^k per unit of energy at time interval k is given as

$$\rho^k = (1+\pi) \cdot \frac{G\left(\sum_{i=1}^{N} x_i^k\right)}{\sum_{i=1}^{N} x_i^k} \qquad (2)$$

where π expresses the profit percentage of the ESP. The bill B_k^i for the energy user i consumes at time interval k and the ESP's income C_N^k are given by

$$B_i^k = \rho^k \cdot x_i^k \qquad (3)$$

and

$$C_N^k = \textstyle\sum_{i=1}^{N} B_i^k , \qquad (4)$$

respectively.

B. *Behavioral Real Time Pricing (B-RTP)*

As mentioned earlier, in section I, this paper considers the use case where the desired voluntary energy consumption $\widetilde{x_i^k}$ of all users $i \in \boldsymbol{N}$ at time interval k is known a priori. Then, the nominal energy bill $\widetilde{B_i^k}$ of user i at time interval k is given as

$$\widetilde{B_i^k} = (1+\pi) \cdot \widetilde{x_i^k} \cdot \frac{G\left(\sum_{i=1}^{N} \widetilde{x_i^k}\right)}{\sum_{i=1}^{N} \widetilde{x_i^k}}, \qquad (5)$$

where π is the % profit of the ESP. We assume that because of an energy program or pricing scheme or other incentive, the desired (voluntary) energy consumption $\widetilde{x_i^k}$ is reduced to his/her actual energy consumption x_i^k according to each user's flexibility (cf. Section II-C) and the pricing model. Thus, at time interval k, each user $i \in \boldsymbol{N}$ reduces her/his energy consumption by $\widetilde{x_i^k} - x_i^k$, leading to an energy cost reduction

$$\Delta C^k = G\left(\sum_{i=1}^{N} \widetilde{x_i^k}\right) - G\left(\sum_{i=1}^{N} x_i^k\right) \tag{6}$$

for the ESP. In B-RTP, each user i is given a discount ΔC_i^k in his/her energy bill at time k, which is calculated as a portion of ΔC^k. In particular, if all the savings ΔC^k of the ESP are proportionally given back to the users as discounts, with the proportions calculated as the ratio between the energy units that user i saved and the total load that is curtailed, we have:

$$\Delta C_i^k = \frac{\widetilde{x_i^k} - x_i^k}{\sum_{i=1}^{N} \widetilde{x_i^k} - \sum_{i=1}^{N} x_i^k} \cdot \Delta C^k \tag{7}$$

Thus, if we wanted to reward user i with the total amount of profits (cost reduction) that her/his behavioral change generated, his/her bill would be:

$$B_{i,BRTP}^k = \widetilde{B_i^k} - (1+\pi) \cdot \Delta C_i^k \tag{8}$$

On the other hand, if we used RTP billing, then the energy bill of user i at time instant k would be:

$$B_{i,RTP}^k = (1+\pi) \cdot G\left(\sum_{i=1}^{N} x_i^k\right) \frac{x_i^k}{\sum_{i=1}^{N} x_i^k}. \tag{9}$$

Note that in that case, a user i who did not reduce his/her consumption $(\text{i.e.}, x_i^k = \widetilde{x_i^k})$, may still benefit from the reduction in the consumption of other users, through the nonlinear decrease in the cost $G(\ )$, something that would be unfair (everybody benefits but only a subset suffers the discomfort). In order to combine the attribute that RTP models have, i.e. to charge end users according to the energy volume that they consume, and the attribute of the B-RTP pricing model that (8) proposes, i.e., to give back the profits obtained from Demand Response to those who really generated them, we propose a hybrid pricing model (also called B-RTP(γ), because of the weighting parameter γ it introduces) which is presented in (10):

$$B_{i,hyb}^k = \widetilde{B_i^k} - (1+\pi) \cdot \gamma \cdot \Delta C_i^k - (1-\gamma) \cdot (\widetilde{B_i^k} - B_{i,RTP}^k) \tag{10}$$

As observed from (10), the hybrid pricing model coincides with RTP model when γ=0. In case that γ=1, we have a fully B-RTP model where the whole cost reduction that is derived from the behavioral change of each user is converted into an equivalent reduction in her/his energy bill. In case 0<γ<1, a fraction γ of the cost reduction that is derived from the behavioral change of each user is converted into discount in her/his bill as in B-RTP, and the remaining (1-γ) fraction is allocated to all participating users as in RTP. In case t γ>1, the hybrid pricing model actually even penalizes the users who do not change their behavior (do not reduce their load) in order to favor even more flexible users. In our evaluation section we demonstrate the impact of the choice of parameter γ in the major Key Performance Indicators (KPIs) of the considered pricing models.

C. User Modeling and B-RTP Development

In order to have a benchmark for the evaluation of B-RTP and the comparison between RTP, B-RTP and Hybrid schemes, we need to have a function that models the degree to which end users value their consumption (equivalently, the degree of discomfort they suffer when they reduce their consumption), expressed in monetary terms (similarly to costs, bills, etc.). In the literature, the concept of utility function has been drawn from the field of Microeconomics [13] for expressing the monetary value of consumption to a user, and is used for the evaluation of pricing schemes in different contexts. A mathematical formula for the utility function $U(x, \omega)$ that has been widely adopted (e.g. [3], [14], [15], [16]) is given by

$$U_i^k(x_i^k, \omega_i^k) = \begin{cases} \omega_i^k \cdot x_i^k - \frac{a}{2} \cdot (x_i^k)^2, & if \ \ 0 < x_i^k < \frac{\omega_i^k}{a} \\ \frac{(\omega_i^k)^2}{2 \cdot a}, & if \ \ x_i^k > \frac{\omega_i^k}{a} \end{cases} \tag{11}$$

In (11), ω_i^k denotes the flexibility (i.e., responsiveness to financial incentives or eagerness to change) of user i at time interval k in terms of reduction of her/his energy consumption, and is a pre-defined parameter that determines the value of energy consumption x to a particular user. Note that utility U_i^k reaches a constant maximum value equal to $(\omega_i^k)^2/(2 \cdot a)$ after a certain saturation point (namely ω_i^k/a), with respect to $\widetilde{x_i^k}$. Two desirable attributes of the aforementioned utility function are that it is increasing and concave. This approach is in line with the vast majority of the literature as well as intuition. Indeed, more consumption should give increasing satisfaction to a user, but at a diminishing rate, and give no satisfaction beyond a certain point. Additional justification for this choice is extensively presented in [10].

In the initial stage of B-RTP development, ESP sets a price vector $\rho^k = \{\rho_i^k, i \in \boldsymbol{N}\}$ for time interval k, based on the desired consumption schedules that users have a priori declared (12). As a response to the price signals from the ESP, users adjust their consumption level according to their flexibility. We assume that each user $i \in \boldsymbol{N}$ is interested in maximizing his own welfare function, which is described in (13). Hence, user i calculates her/his consumption schedule by solving (14). Consequently, ESP takes as input all users' consumption schedules and re-calculates the prices according to (15).

$$\rho_i^k = \frac{\widetilde{B_i^k}}{\widetilde{x_i^k}} \tag{12}$$

$$W_i^k = U_i^k - \rho_i^k \cdot x_i^k \tag{13}$$

$$x_i^k = arg \max_{x_i^k} \{W_i^k\}, \qquad \forall k \in \boldsymbol{H} \tag{14}$$

$$\rho_i^k = \frac{B_i^k}{x_i^k} \tag{15}$$

Note that each user receives a generally different price according to his/her energy behavior. The aforementioned procedure is repeated through message exchanges between the

ESP and its clients. Users take turns sequentially and the algorithm converges to the Nash Equilibrium as proved in theorem 2 of [17]. The algorithms of B-RTP and RTP schemes are summarized in Tables I and II respectively.

It is important to note that the utility function is used to model the users' behavior in the performance results, but in practice it does *not* really have to be known for the schemes to be implemented. A user i may simply reply to a price offer ρ_i^k with an actual consumption x_i^k, without doing any calculations or knowing his/her utility functions, simply from his own behavioral will (utility essentially models user's behavior).

TABLE I. ALGORITHM FOR THE PRICE AND THE ENERGY CONSUMPTION CALCULATION IN B-RTP

1	**Initialization:** j**=1,** $x_i^{k,j}=\widetilde{x_i^k}$, $\rho_i^{k,j}=\frac{\widetilde{B_i^k}}{x_i^{k,j}}$ $\quad \forall i \in N, k \in H$
2	**Repeat**
3	**for** each user $i \in N$
4	receive $\rho_i^{k,j}$
5	**Repeat**
6	Update $x_i^{k,j}$
7	Update $\rho_i^{k,j}$ using (15)
8	Calculate W_i^k using (13)
9	**until** reach solution of (14)
10	**end for**
11	Calculate *divergence*=max$\left\lvert x_i^{k,j+1} - x_i^{k,j} \right\rvert$ $\quad \forall i \in N$, $k \in H$
12	**Until** *divergence < desired accuracy*
13	**End**

TABLE II. ALGORITHM FOR THE PRICE AND THE ENERGY CONSUMPTION CALCULATION IN RTP

1	**Initialization:** j=1,$x_i^{k,j}=\widetilde{x_i^k}$, $\rho^{k,j}=\frac{\widetilde{B_i^k}}{x_i^{k,j}}$ $\quad \forall i \in N, k \in H$
2	**Repeat**
3	**for** each user $i \in N$
4	receive $\rho^{k,j}$
5	**Repeat**
6	Update $x_i^{k,j}$
7	Update $\rho^{k,j}$ using (2)
8	Calculate W_i^k using (13)
9	**until** reach solution of (14)
10	**end for**
11	Calculate *divergence*=max$\left\lvert x_i^{k,j+1} - x_i^{k,j} \right\rvert$ $\forall i \in N$, $k \in H$
12	**Until** *divergence < desired accuracy*
13	**End**

III. PERFORMANCE EVALUATION RESULTS

In this section, we evaluate our proposed B-RTP and hybrid schemes and we compare them with the RTP approach. For this purpose, we considered a system of N = 10 users and we conducted simulations with various values of γ and π. The parameters ω in the users' utility functions were uniformly selected for each user i within the interval [50,250]), while parameter a was set to 5. Energy cost function parameter c is set to 0.02. Since we deal with only consumption curtailments, our system is memoryless. Therefore, users' scheduling problem (Tables I, II) can be solved independently for each timeslot k. In order to assess the performance of our algorithm, we used the following Key Performance Indicators (KPIs):

- Energy Cost G, as defined in (1), which is the cost of ESP to purchase the electricity needed to fulfill the requirements of customers/consumers. This is an index of how efficient a pricing strategy is in terms of incentivizing its customers to curtail their consumption.
- Aggregate Users' Welfare (AUW) is a KPI that expresses the aggregated value of each user's welfare as defined in (13) :

$$AUW = \sum_{i=1}^{N}\left(U_i^k - \rho_i^k \cdot x_i^k\right) \qquad (16)$$

- Total Welfare (TW) is defined as the summation of AUW and ESP's profits. It is a measure of the system's efficiency and is used extensively (e.g. [3], [14]) in the literature:

$$TW = AUW + \sum_{i=1}^{N}\left(\rho_i^k \cdot x_i^k\right) - G \qquad (17)$$

First, we examine the case of a fully B-RTP scheme, where the energy cost reduction that users achieve is entirely converted into a discount in their energy bills (γ = 1) and we compare it to the RTP case. In Fig. 1, we present the ratio between the Energy Cost with B-RTP and the Energy Cost with RTP as a function of ESP's profit percentage π. We observe that B-RTP achieves reduced energy cost (7%-14% savings) when it is compared to RTP. In fact, the energy cost appears to decline in a linear fashion with increasing π. This is because B-RTP, by being fair and benefiting users who contribute to cost reduction, is more successful in motivating users to reduce more their demand and consequently the energy cost of ESP.

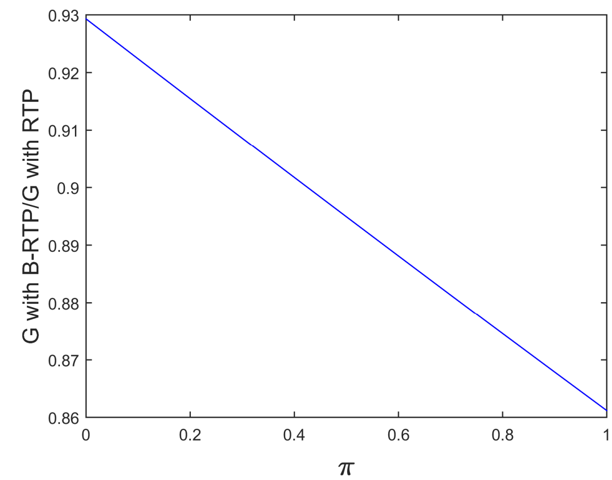

Fig. 1: Ratio between G for B-RTP(γ) and for RTP as a function of π

Fig. 2 depicts AUW for both B-RTP (γ=1) and RTP as a function of π. It is interesting to note that the B-RTP scheme, while accomplishing a significant cost reduction, still achieves a slightly better *AUW* (user welfare, defined as user satisfaction minus cost), as the users are rewarded with higher reduction in their energy bills than with RTP.

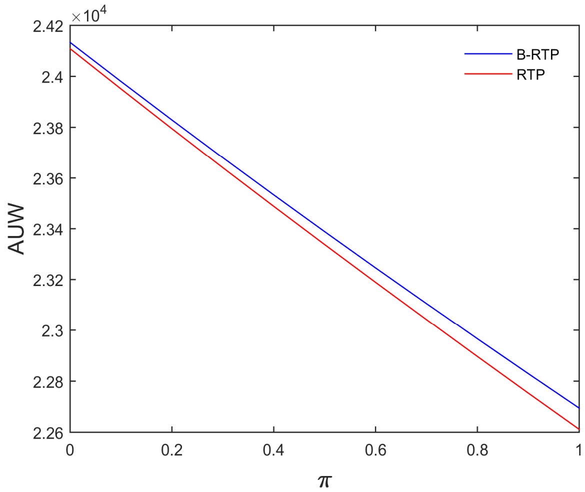

Fig. 2: *AUW* of B-RTP(γ) and RTP as a function of π

The adaptability of the Hybrid (i.e., B-RTP(γ)) scheme gives the ESP the opportunity to select its own strategy with respect to users' reward, by adjusting properly the value of γ. As discussed earlier, high values of γ imply higher rewards for flexible users, hence lower consumption levels. Indeed, through Fig. 3, which depicts the ratio between the electricity cost with hybrid B-RTP(γ) and the electricity cost with RTP as a function of γ, we see that an ESP can reduce its energy cost by increasing γ. The value of π in these simulations was 0.2.

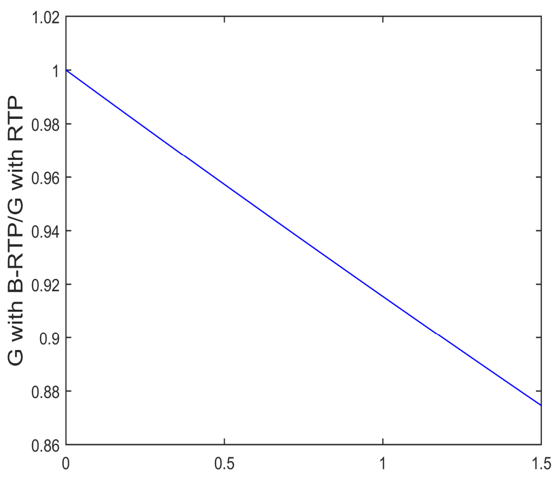

Fig. 3: Ratio of *G* for B-RTP(γ) over *G* for RTP as a function of γ

Fig. 4 and Fig. 5 depict the ratio between B-RTP and RTP for the *AUW* and the *TW* metrics, respectively. As can be seen in Fig. 4, lower energy costs do not imply lower *AUW* comparing to the RTP case, when B-RTP is implemented. In fact, B-RTP accomplishes almost negligible but yet slightly higher *AUW* than RTP for the values of γ that we examine (0 to 1.5). This is explained by the fact that the flexible users' utility may decline (in comparison to RTP), but their compensation is even higher, and therefore their total welfare does not diminish. In case of *TW* (Fig. 5), the difference between the two models is insignificant (<0.01%). Therefore, the proposed pricing scheme achieves a reduction in the system's cost (Fig. 1 & 3) without compromising *AUW* or *TW* (Fig. 4 & 5).

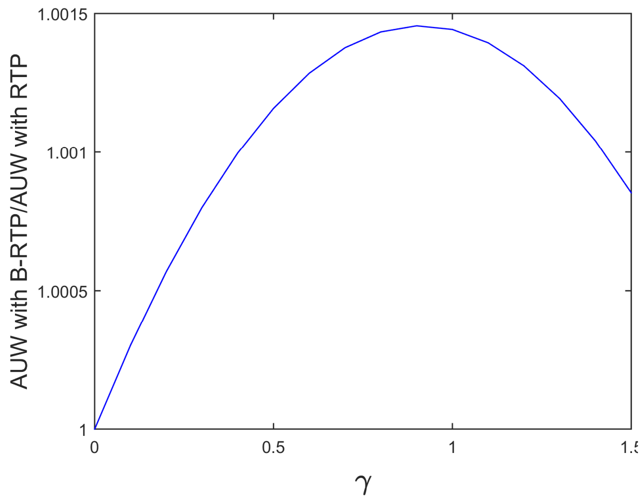

Fig. 4: Ratio between *AUW* of B-RTP(γ) and *AUW* of RTP as a function of γ

For even higher values of γ (γ>1,5), *G* declines even further, without an analogous *TW* and *AUW* reduction. This, however, would occur at the expense of welfare of the users who choose not to markedly shed their demand. These users would be penalized for their inelasticity in order for the flexible users to receive a massive bonus for their behavior. In order to demonstrate this, we conducted five simulation experiments for corresponding values of γ in the set {0, 0.5, 1.0, 1.5, 2.0}. Fig.

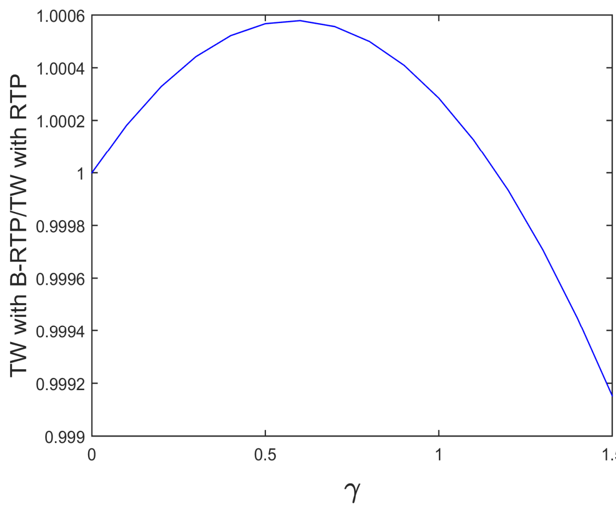

Fig. 5: Ratio between *TW* of B-RTP(γ) and *TW* of RTP as a function of γ

6 depicts the ratio between Users' Welfare in all the aforementioned cases and in case where γ=1, as a function of the elasticity ω of users. We observe that larger values of γ lead to higher welfare for the more flexible users, which is not the case for inflexible users. Each inflexible user contributes to a slight degree to the increase of flexible user's welfare. In conclusion, the higher value of γ the ESP chooses, the more it incentivizes the users to shed their consumption. As we observe in Fig. 6, RTP (γ=0), in contrast with B-RTP, neither incentivizes the less flexible users to follow the example of the flexible ones, nor rewards properly the latter.

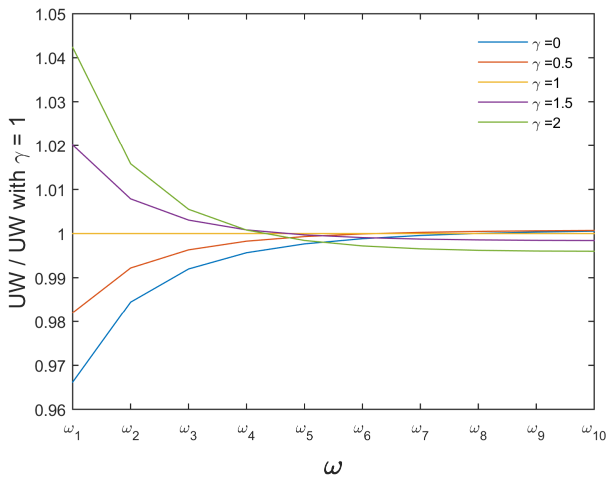

Fig. 6: Ratio between Users' Welfare for several values of γ and Users' Welfare for γ=1, as a function of ω

IV. CONCLUSION

In this paper, we focused on modern energy pricing models, including RTP, and argued that they do not fairly reward flexible users who are willing to modify their energy behavior, as they benefit equally and indiscriminately all users. Thus, existing pricing models are not designed to trigger behavioral changes as they treat unfairly end users eager to respond to them. Incentivized from this observation, we developed a Behavioral Real Time Pricing (B-RTP) algorithm, which disposes an adjustable level of rewarding by offering financial incentives to participating users to change their behavior. We assume in this work that the desired ECC is a priori known and we model only energy consumption curtailments (sheds). Our evaluation presents a comparison between RTP and parameterized B-RTP(γ), which shows that our proposed B-RTP affects the behavior of the participating users much more effectively than RTP. In our future work, we will extend B-RTP in order to account for energy consumption shifts, additionally to energy consumption sheds and we will advance its model in order to take into account use cases where the desired ECC is unknown. Finally, we plan to study the impact of the implementation of B-RTP in islanded microgrids, in terms of RES and ESSs investment costs (sizing).

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