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# Real-time pricing in environments with shared energy storage systems

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**Abstract** A major challenge in modern energy markets is the utilization of energy storage systems (ESSs) in order to cope up with the difference between the time intervals that energy is produced (e.g., through renewable energy sources) and the time intervals that energy is consumed. Modern energy pricing schemes (e.g., real-time pricing) do not model the case that an energy service provider owns a shared ESS that its customers could take advantage of, even though a shared ESS is more efficient than the operation of many individual ESSs (i.e., personal ESS case). Thus, we propose a shared ESS aware real-time pricing model that achieves a very attractive tradeoff between the service provider's and end user's interests. We also compare our system with its predecessors and we witness its superiority. The proposed scheme allows energy consumers to use shared ESS and have cost-efficient energy services and in the same time they protect their interests (fair billing).

**Keywords** Smart grids · Demand response program · Shared energy storage system · Real-time pricing · Energy consumption scheduling

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## Introduction

The projected growth in global electricity demand (USEIA 2016), the global concerns for the environment, and the conditions in the global economy (USEPA 2017) combined with the increasing use of information and communication technologies (ICT) are motivating the transition from a centralized grid to a decentralized, dynamic, and flexible grid (Smart grid). The Smart Grid concept (Farhangi 2010), which includes the modernization of the existing power network through the ICT contribution, aims at the efficient energy usage and the reduction of the total energy cost.

In this context, the use of energy storage technologies to address production and consumption fluctuations can provide an alternative solution to the costly conventional thermal generators and lead to a more flexible and resilient grid. The implementation of energy storage systems (ESSs) can bring various advantages, such as grid

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operational cost savings, reliability improvement, $CO_2$ emissions reduction, and job creation. Currently, the application of ESSs in Smart Grids is receiving more attention than ever from system operators, since ESSs are experiencing a substantial growth in their performance and operational efficiency, along with a continuous CAPEX reduction during the last years (Deutsche Bank 2015; World Energy Council 2016), while the integration of renewable energy sources makes production more distributed, dynamic, and unpredictable. Various battery models (TESLA 2016; LG Chem 2016; Eaton Nissan 2017; SonnenBatterie 2017) are manufactured for residential and commercial use. However, due to both high purchase/installment costs and space limitation, the solution of integrating a shared ESS to serve an energy community is more efficient than individual ESS operation. The concept of "shared" ESS includes two cases. In the first case, a company, such as an energy service provider (ESP), installs at its premises (or leases) and operates a bulk ESS. In the second case, the ESP installs and centrally controls small ESSs at users' premises. In the context of the first case, HENBO energy storage (Henbo 2015) has already installed a shared ESS in Upperlands, Northern Ireland, in order to demonstrate the high value of combining renewable energy generation with a shared ESS. Moreover, Tesla is planning to build the world's largest shared ESS in South Australia with the objective being to increase local electricity grid reliability and stability (Edelstein 2017). In this paper, we adopt the case in which a bulk ESS is installed and controlled by an ESP in such a way that ESS benefits are fairly distributed among the users. It is proved by Rahbar et al. (2016) that the installment of a shared ESS increases the end-users' profits even by 10% in comparison with the individual ESSs case. Moreover, our recent work in (Tsaousoglou et al. 2016) demonstrates that a virtual storage bank, consisting of several individual storage capacities, can increase the profit by up to 15.5–16.5% in comparison with distributed ESSs operating independently. Thus, a shared ESS can reduce the energy costs of the ESP and at the same time benefit the users in terms of convenience and energy bills. The main challenge for the ESP is how to operate optimally the shared ESS. Thus, intelligent ESS control strategies are needed so as not to risk the smooth grid operation, especially at peak hours (or harmonize production with consumption in case of high RES penetration).

A method toward this goal (modify the aggregate energy consumption curve (ECC) in order to reduce the energy cost) is demand side management (DSM). DSM includes, among others, smart energy pricing schemes in order to incentivize the energy consumers toward a consumption pattern that provides a good trade-off between their desired pattern and the one that is cost-efficient for the energy system (Palensky and Dietrich 2011). A great deal of recent research has focused on developing new, smarter pricing models with the purpose of arousing the users' demand response (DR) capabilities (Khan et al. 2016). The most common flat price model provides no monetary motivation for the users to re-shape their consumption curve, while the follow up model of inclining block rates, although it drives users toward a lower total consumption, it still does not guarantee that it is able to give back to the energy producers the exact cost of energy (Mohsenian-Rad and Leon-Garcia 2010). Consequently, the introduction of time of use (ToU) models motivates consumers to shift loads into low pricing hours; however, they are still static and the prices do not reflect the real-time state of the grid (prices are calculated a priori through estimations and users are just price takers). Thus, it often results in congestion problems during the low-price hours. Recently, real-time pricing (RTP) models (Meng and Zeng 2013; Samadi et al. 2010; Li et al. 2011) were proposed in order to directly connect the generation, transmission, and distribution costs to the retail price and essentially reduce the peak-to-average ratio of a set of users. Toward the realization of RTP, the first step is the development of a two-way communication system between the ESP and the end-users. Then, through a limited number of message exchanges, prices are derived in real time resolving the trade-off between the electricity cost minimization and the users' comfort maximization (Samadi et al. 2010; Li et al. 2011).

A pricing model has to fulfill several requirements (by achieving an attractive trade-off) that is related with (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 pricing model. The first one is denoted as *user's welfare* and is formulated according to the difference between a utility function that expresses how much an end user values a specific consumption pattern and the actual cost of energy that it consumes. In the context of the comparison of two pricing schemes, user's welfare expresses which pricing scheme leads to more competitive services in the open market. The second requirement is

denoted as *behavioral efficiency* and expresses the capability of a pricing scheme to achieve the objectives (e.g., load curtailments and shifts) which motivates. Intuitively, behavioral efficiency of a pricing scheme expresses how friendly it is to a TSO/DSO (issues relevant with energy network stability, efficiency, and costs) and implicitly affects several financial metrics (e.g., investments in RES, energy storage, and network upgrades). *Fairness* (in terms of rewarding the users that modify their consumption) is a necessary condition toward behavioral efficiency. Usually, it is also linked with minimizing the system's energy cost. The third requirement is denoted as *profit dynamics* and it represents the profit percentage per energy unit and the total revenues of the ESP. In other words, it expresses the financial growth potential of the ESP that deploys a specific pricing scheme.

While RTP motivates energy consumption changes that reduce energy cost, the shared ESS (without an appropriate pricing scheme) may act as a substitute and some of energy cost reduction DR operations (shift or curtailment of devices' power consumption) are not adequately incentivized (Jiang et al. 2014; Koutsopoulos et al. 2011; Codemo et al. 2013; Nguyen and Le 2014). In this paper, we jointly design the ESS optimal operation strategy along with an ESS-aware RTP model and thus we make the better of both available tools (ESS operation and DR actions) toward a more efficient energy scheduling. The proposed model is also able to achieve high fairness (behavioral efficiency) without sacrificing at all users' welfare and profit dynamics.

The rest of the paper is organized as follows. In "Related work" section, we briefly discuss on the related work and we highlight the contributions of this paper. In "System model" section, we present the way that we model the proposed system again according to the recent literature. In "Problem formulation and proposed algorithm" section, we propose our innovative ESS aware RTP scheme. In "Performance evaluation" section, we evaluate our proposed system and we compare it with existing systems in recent literature. Finally, in "Conclusions and future work" section, we conclude and discuss future work.

## Related work

There exists a significant amount of work on energy management solutions that integrate ESSs. In some cases, ESSs are operated by individuals and in other works users are considered to take advantage of a shared ESS that is usually offered by their ESP. In the former case, each user operates the ESS according to her interest while in the latter, the total cost is reduced due to the multiplexing of the ESS's use. This necessitates the development of a fair pricing scheme that will allow consumers to use shared ESS and in the same time protect their interests. In both cases, users could also optionally participate in DR programs (e.g., ToU, RTP) and could be thus motivated to modify their desired consumption.

There are systems that mainly focus on the personalized use of an ESS. In more detail, researchers (Li et al. 2011; Jiang et al. 2014; Omowunmi et al. 2017; Atzeni et al. 2013a, b; Nguyen et al. 2015) consider systems where energy consumers who own residential ESSs participate in DR programs. In the work of Omowunmi et al. (2017), users schedule their flexible loads and their personal ESS in order to maximize their profit under a ToU pricing scheme. Atzeni et al. (2013a, b) proposed a non-cooperative and a cooperative game among energy prosumers, who schedule their ESS charging/discharging and their prosumption pattern. The objective in the first case is the minimization of the individual energy cost and in the second case, the minimization of the total energy cost. Researchers in Nguyen et al. (2015) developed a game-theoretic system in which users (who possess ESSs) exchange information with the ESP in order to optimally schedule their consumption and their ESS operation by maximizing their welfare. Li et al. (2011) and Jiang et al. (2014) considered users owning residential ESSs. An ESP sets a price (according to a RTP model) and users respond by selecting their consumption curve and operating their ESS in a way that both maximize their welfare. Finally, researchers in (Alam et al. 2017) propose a combination of a DSM program and a Peer-to-Peer (P2P) energy trading model, where users leverage distributed renewable energy generation, residential ESSs, and their demand flexibility in order to minimize the total system cost.

Taking into consideration the ESS market prices, a reasonable solution is the sharing of an ESS among several energy users. Rahbar et al. (2016) demonstrated that a shared ESS can potentially increase the total users' profit compared to the case of personal (distributed) ESS. ESS is supervised by a central controller, who distributes the financial benefit of the ESS equally among the participating users (in terms of energy cost reduction). Moreover, researchers in (Koutsopoulos et al. 2011;

Codemo et al. 2013; Parisio and Glielmo 2011; Paridari et al. 2015) considered an ESP operating a shared ESS. In Koutsopoulos et al. (2011) and Rahbar et al. (2015), the optimal control of an ESS is studied in order to minimize the cost of energy that is purchased from the main grid. Furthermore, Codemo et al. (2013) studied the energy cost minimization problem in the presence of a shared ESS and proposed four different algorithmic solutions. In all the above works, users do not participate in a DR program and therefore they are not motivated to alter their desired consumption pattern. In order to further reduce energy costs and consumption curve fluctuations, DR programs have been also considered in the literature. In Parisio and Glielmo (2011), Bahramirad et al. (2012), and Zhang et al. (2013), the microgrid (MG) scheduler operates a shared system of generation units and a shared ESS in order to optimize the operation of the MG. In order to further reduce MG's costs, the MG operator applies direct control on consumers' loads, with the disadvantage of substantial reduction of users' welfare. Finally, Paridari et al. (2015) considered a shared ESS, which is controlled by an aggregator with the aim of minimizing the aggregated energy cost. The aggregator's DR strategy is to financially incentivize the users in order to modify their consumption.

In addition to the aforementioned works, in this paper, we propose a comprehensive model to jointly optimize the users' flexible loads and the ESS operation, along with an ESS-aware fair RTP scheme (*F-RTP-S*) that interact (users pay the exact cost of energy that they consume). Thus, the major innovations of this paper are:

- The design of an architecture that integrates advanced pricing schemes that incentivize behavioral changes (i.e., RTP) and a shared ESS.
- The creation of an innovative pricing model (*F-RTP-S*), which disposes high fairness (end users pay the exact energy cost that they consume) without sacrificing at all users' welfare and ESP's profit dynamics.
- The comparison of the proposed pricing model (*F-RTP-S*) with the conventional RTP and the RTP in environments with shared ESS (*RTP-S*).

To the best of our knowledge, this is the first work that co-designs an optimal shared ESS operation and an ESS-aware real-time pricing scheme, so that it makes the best out of both the ESS operation and the users' DR capabilities.

## System model

We assume an ESP that participates in the energy wholesale market to purchase energy. The model and the operation of the market that we envisage is described and modeled theoretically by Roozbehani et al. (2010) and Kothari and Nagrath (2003). In addition, ESP leverages a shared ESS, installed at its premises, in order to offer to its clients (energy consumers) services with better quality (lower energy cost). This means that the ESP is able to buy energy from the wholesale market in a specific time instant and store it in order to provide it to its users in a future moment. In this work, we do not consider the participation of the ESP in flexibility markets (balance and congestion market). We consider it an orthogonal problem and we refer to Makris et al. (2018) and Tsaousoglou et al. (2017) for a more detailed study in this issue (Table 1).

We consider a discrete-time model with a finite horizon $H$ that models a day. Each day is divided into $T$ timeslots of equal duration. The proposed architecture is depicted in Fig. 1, where a set $\boldsymbol{N} = \{1,..,N\}$ of users (ESP's clients) are connected with the main grid directly and through the ESP's ESS. The ESP participates in wholesale markets during slot $k$ to purchase $g^k$ units of electricity from generators, and then sell $x^k - r^k$units to its $N$ customers in the retail market or charge (the word charge in this paper exclusively means energy transfer to the ESS and not billing) the ESS with $r^k > 0$ units ($r^k < 0$ corresponds to discharging the ESS). In order to minimize the total cost, ESP optimally operates the ESS and calculates a price vector $\rho = \{\rho^1,..,\rho^k,..,\rho^T\}$ (see "Problem formulation and proposed algorithm" section), which it communicates to its clients through a communication network lying on top of the electric grid. Every user possesses a smart meter and an energy scheduling unit, which schedules her flexible appliances by maximizing her welfare (cf. "Problem formulation and proposed algorithm" section). Then, each user $i$ informs ESP about her decided schedule $x_i = \{x_i^1, .., x_i^k, .., x_i^T\}$ and ESP responds to users' signal with the updated prices and adjusts the charging/discharging ESS schedule (cf. "Problem formulation and proposed algorithm" section). This iterative process continues, until the system reaches a state of convergence.

In the rest of this section, the model of each component of the aforementioned architecture is presented.

**Table 1** Notation

| Notation | |
|---|---|
| $i$ | End user index |
| $k$ | Time slot index |
| $k\_ch$ | Index of time slots in which ESS is charged |
| $k\_dis$ | Index of time slots in which ESS is discharged |
| $j$ | Algorithm iteration index |
| $N$ | Set of end users |
| $H$ | Set of time slots (Scheduling Horizon) |
| $\widetilde{H_{s,i}}$ | Desired load time schedule of user $i$ |
| $N$ | Total number of end users |
| $T$ | Total number of time slots |
| $\tilde{t}_i^a$ | Desired load's plug in timeslot of user $i$ |
| $\tilde{t}_i^b$ | Desired load's task finishing timeslot of user $i$ |
| $t_i^s$ | Earliest acceptable timeslot for user' $i$ load to start operating |
| $t_i^l$ | Latest acceptable timeslot for user' $i$ load to finish operating |
| $B$ | Storage capacity |
| $S_{min}$ | Minimum amount of energy stored in the ESS allowed |
| $S_{max}$ | Maximum amount of energy stored in the ESS allowed |
| $S^k$ | Amount of energy stored in the ESS at the beginning of time slot $k$ |
| $r^k$ | The amount of energy charged from ($r^k \geq 0$) or discharges to ($r^k < 0$) the grid at time slot $k$ |
| $V^k$ | Sunk cost of the stored energy in ESS at the beginning of time slot $k$ |
| $\eta_c$ | Charging efficiency parameter |
| $\eta_d$ | Discharging efficiency parameter |
| $g^k$ | Total energy drawn from the main grid in time slot $k$ |
| $x_i$ | Energy consumption schedule of user $i$ |
| $x_i^k$ | Energy consumption of user $i$, at time slot $k$ |
| $x^k$ | Aggregate energy demand at time slot $k$ |
| $\tilde{x}_i$ | Desired energy consumption schedule of user $i$ |
| $\tilde{x}_i^k$ | Desired energy consumption of user $i$, at time slot $k$ |
| $\overline{x_i^k}$ | Predicted energy consumption of user $i$, at time slot $k$ |
| $x_{i\_}^k$ | Lower bound of user's $i$ consumption at time slot $k$ |
| $x_{i,RTP}^k$ | Energy consumption of user $i$, at time slot $k$ in case of RTP |
| $\tilde{E}_i$ | Desired cumulative energy consumed by user's $i$ "type B' load |
| $E_{i\_}$ | Lower bound of cumulative energy consumed by user's $i$ "type B" load |

**Table 1** (continued)

| Notation | |
|---|---|
| $U_i^k(x_i^k)$ | Utility function of user $i$, at time slot $k$ in case of loads of "type A" |
| $\omega_i^k$ | Elasticity parameter of user $i$, at time slot $k$ in case of loads of "type A" |
| $a_i^k$ | Predetermined parameter of utility function in case of loads of "type A" |
| $U_{max,\ i}$ | Maximum utility attained by user $i$ from the operation of loads of "type B" |
| $\delta_i$ | Elasticity parameter of user $i$, at time slot $k$ in case of loads of "type B" |
| $C$ | Conventional generation cost function |
| $c$ | Parameter of the cost function |
| $\pi$ | ESP profit percentage |
| $\rho$ | Vector of prices through the scheduling period |
| $\rho^k$ | Price per unit of energy at time slot $k$ |
| $\rho_{RTP}^k$ | Price per unit of energy at time slot $k$ in case of RTP |
| $G$ | Total energy cost |
| TW | Total welfare |
| AUW | Aggregate users' welfare |
| EP | Profit of ESP |
| TF ($k$) | Time fairness |
| UF ($i$) | User fairness |
| $UB_i$ | User's $i$ energy bill |
| $UFB_i$ | User's $i$ fair energy bill |
| $UB_{o,i}$ | User's $i$ energy bill with no shared ESS installed |
| SB | The benefit that an ESS produces |
| SoD | Savings of ESS Discharge |
| CoC | Cost of ESS Charge |
| $SBD_i$ | User's $i$ dividend of the benefit that an ESS produces |

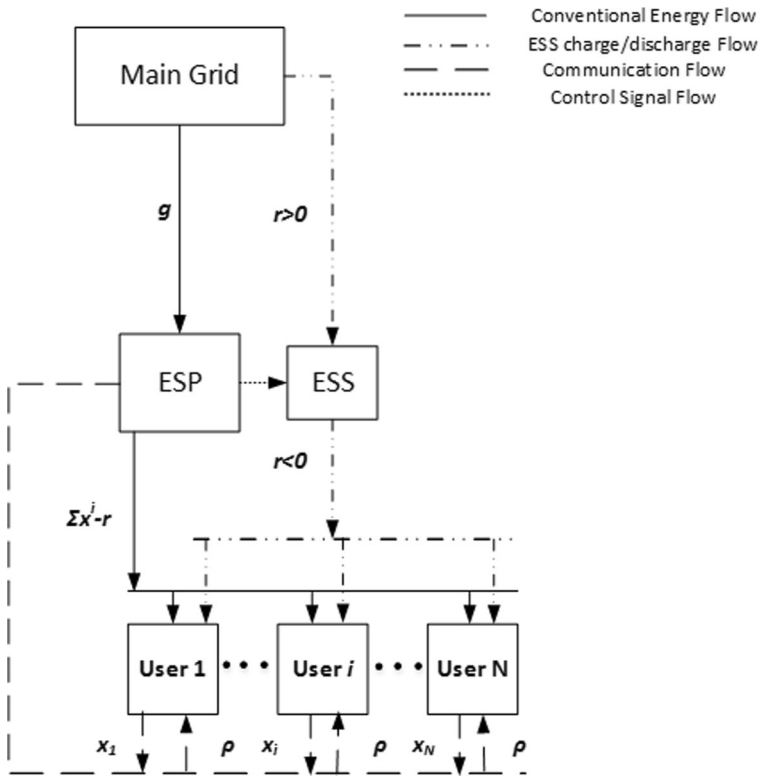
## Energy storage model

We consider an ESS of capacity $B$ installed by ESP. We denote as $S^k$ the amount of the energy stored in the ESS at the beginning of time slot $k$ (i.e., initialization phase). In order to avoid overcharging, there is an upper bound $S_{max}$. A lower bound $S_{min}$ is used to avoid deep discharging (Shi et al. 2015; Huang et al. 2014). Hence:

$$S_{min} \leq S^k \leq S_{max}, \quad k = 1, 2, \ldots, T \tag{1}$$

For the energy balance of the ESS the energy $S^T$ that is stored inside the ESS at the end of the scheduling period $H$ is set the same as the initially stored energy $S^I$ (Vytelingum et al. 2010; Chen et al. 2011; Atzeni et al. 2013a, b; Abbey and Joos 2009). Thus:

**Fig. 1** System model




$$S^{T+1} = S^1 \tag{2}$$

Additionally, we denote as $r^k$ the quantity of energy that is charged (if $r^k \geq 0$) to or discharged (*if* $r^k < 0$) from the ESS at time slot $k$. In practice, there are energy losses during both the charging and the discharging procedures, which can be specified by the charging ($\eta_c$) and discharging ($\eta_d$) efficiency parameters, where $0 \leq \eta_c \leq 1$ and $0 \leq \eta_d \leq 1$. We assume that battery power leakage is negligible and power converter losses are lumped with battery (dis) charging efficiency. According to these, we use the following equation in order to model the storage dynamics by respecting the aforementioned constraints:

$$S^{k+1} = \begin{cases} S^k + \eta_c * r^k, & \text{if } r^k \geq 0 \\ S^k + {r^k}/{\eta_d}, & \text{if } r^k < 0 \end{cases} \tag{3}$$

In each time slot $k$, the discharged energy is used by the users. According to it, the ESS cannot discharge more energy than the users need. Thus:

$$\left|r^k\right| \leq \sum_{i=1}^{N} \overline{x_i^k}, \quad \text{in case that } r^k < 0 \tag{4}$$

In Eq. (4), $\overline{x_i^k}$ is the predicted amount of energy that user $i$ will consume at time instant $k$. This work assumes that users state their demands and this constitutes them perfectly predicted. The case of inaccurate predictions is analyzed in Tsaousoglou et al. (2017), Steriotis et al. (2018), Makris et al. (2018), and Chapman and Verbic (2017). Moreover, in our previous work (Tsaousoglou et al. 2017), we analyze the robustness of our proposed model with respect to inaccuracies in the predictions. The proposed algorithms of this work are orthogonal to the solutions analyzed in the references above and thus the latter can be applied on top of the former ones. Therefore, hereinafter we will exclusively use variable $x_i^k$ when we refer to user's $i$ demand at timeslot $k$.

In practice, there are costs related to the ESS, such as installment, operational, and aging costs, which should be accounted for the long-term battery management. However, these factors are not taken into account for our investigation of real-time energy storage scheduling over a relatively short time horizon. We will incorporate these factors in our future studies as they do not have a qualitative impact in the existing work. Finally, we assume that there exist no delays in the energy transactions between the grid and the ESS.

Load in systems with ESS

In each time slot $k$, the $N$ energy consumers have total energy demand $x^k = \sum_{i=1}^{N} x_i^k$. The energy drawn from the main grid at time $k$ is $g^k$. Since the total demand has to be met from the proposed system in every time slot, we have:

$$g^k = x^k + r^k \tag{5}$$

Conventional energy cost

ESP supplies its customers with energy by purchasing it from the main grid (wholesale market). The cost of the energy $g^k$ that is drawn from the main grid is given by function $C(g^k)$, which is usually assumed in the literature (Samadi et al. 2010; Koutsopoulos et al. 2011; Rahbar et al. 2015; Mohsenian-Rad et al. 2010) to be quadratic:

$$C\left(g^k\right) = (1+\pi)\cdot c\cdot\left(g^k\right)^2 \quad \forall k \in \boldsymbol{H} \tag{6}$$

In Eq. (6), $c$ is a cost parameter, $C(g^k)$ represents the ESP's cost to buy an amount of energy equal to $g^k$, and variable $\pi$ represents the percentage of profit that ESP has.

Energy consumers—utility function

Each consumer $i \in N$ independently chooses her consumption pattern, taking into account the electricity price vector $\rho$ that ESP communicates to her. However, not all consumers value consumption in the same way. In order to evaluate our proposed system, we utilize the concept of utility function from the field of Microeconomics (Mas-Colell et al. 1995) to model a consumer's satisfaction (expressed in monetary value) regarding her electricity consumption. For the sake of our study's completeness, we consider two scenarios: (A) users' flexible loads fall into the "*Type A*" category of devices that users care about how much power they consume at each timeslot (e.g., HVAC systems, lighting, etc.); (B) users operate flexible appliances of "*Type B*" such as electric vehicles (EVs), for which they care about the cumulative energy that these devices consume through the entire scheduling period. Without loss of generality, we consider users operating one flexible load. This work can be easily extended in order to include users operating more than one flexible appliance.

*Loads of "type a"*

In order to model users owning flexible loads of "type A" and evaluate our proposed system, we adopt an analytic expression $U_i^k\left(x_i^k, \omega_i^k\right)$ for the utility function that is widely used in the literature (Samadi et al. 2010; Ma et al. 2014; Zhang et al. 2014) and is flexible enough to model the behavior of different users (Samadi et al. 2010) in terms of responsiveness to monetary incentives. In the aforementioned works, the utility function's general form is the same for every user $i \in N$ and in each time slot $k \in H$ and is given by

$$U_i^k\left(x_i^k, \omega_i^k\right) = \begin{cases} \omega_i^k * x_i^k - \dfrac{a_i^k}{2} * x_i^{k\,2}, & if\ 0 < x_i^k < \dfrac{\omega_i^k}{a_i^k} \\ \dfrac{\left(\omega_i^k\right)^2}{2 * a_i^k}, & if\ x_i^k > \dfrac{\omega_i^k}{a_i^k} \end{cases} \tag{7}$$

In Eq. (7), $\omega_i^k$ is a parameter that expresses the degree to which user $i$ is affected by financial incentives to alter (shed) her consumption in timeslot $k$. The lower the value of $\omega_i^k$ is, the more responsive (flexible) the user $i$ is to price in time $k$. Figure 2 depicts utility of user $i$ at time slot $k$ as a function of $x_i^k$ for three different values of $\omega_i^k$ ($\omega_1 < \omega_2 < \omega_3$). The above mathematical expression of $U_i^k\left(x_i^k, \omega_i^k\right)$ satisfies two desired properties:

1. User's satisfaction increases with energy consumption.
2. After a certain level of consumption, user's satisfaction gets saturated.

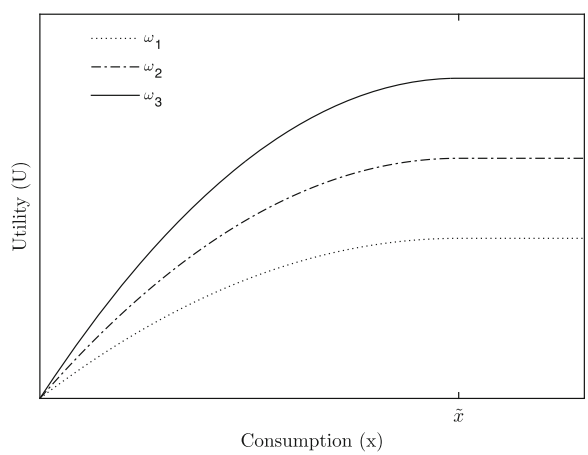



**Fig. 2** Consumer's utility as a function of consumption for different values of ω ($\omega_1 < \omega_2 < \omega_3$)

The above assumptions are satisfied by the given choice of $U_i^k(x_i^k, \omega_i^k)$ being increasing and concave, respectively. In Eq. (7), $a_i^k$ is a predefined parameter. We consider the utility function's saturation point as the user's desired consumption, which is denoted as $\widetilde{x_i^k}$. Thus, parameter $a_i^k$ is calculated through Eq. (8) below:

$$a_i^k = \frac{\omega_i^k}{\widetilde{x_i^k}} \tag{8}$$

The aggregate utility that user $i$ attains through the scheduling period is $U_i = \sum_{k=1}^{T} U_i^k$. In the case of "type A" flexible loads, consumers declare to their EMSs the upper (desired) and the lower bounds or their loads power consumption at each timeslot:

$$\underline{x_i^k} \le x_i^k \le \widetilde{x_i^k}, \quad \forall k \in \boldsymbol{H} \tag{9}$$

*Loads of "type B"*

In this scenario, an electricity consumer $i$ sets her desired operating schedule $\widetilde{x_i} = \left\{\widetilde{x_i^1}, .., \widetilde{x_i^k}, .., \widetilde{x_i^T}\right\}, k \in \widetilde{H_{s,i}}$, where $\widetilde{H_{s,i}} = \left[\widetilde{t_i^a}, \widetilde{t_i^b}\right]$ is a time interval where $\widetilde{t_i^a}$ is the timeslot at zwhich it is desirable for the load to start and $\widetilde{t_i^b}$ is the timeslot at which it normally finishes its task if it starts operation at $\widetilde{t_i^a}$. Additionally, she sets a time constraint $t_i^s$, which is the earliest time in which her EMS is allowed to set the load to start its task and a deadline $t_i^l$, which is the latest time by which the task of her load should be completed. Furthermore, she declares the upper (desired) and lower bounds of the load's power consumption at each timeslot along with the upper (desired) and the lower bounds of the load's cumulative energy consumption along with:

$$\underline{x_i^k} \le x_i^k \le \widetilde{E}_i, \quad \forall k \in \left[t_i^s, t_i^l\right] \tag{10}$$

$$\underline{E_i} \le \sum_{k=t_i^s}^{k=t_i^l} x_i^k \le \widetilde{E}_i \tag{11}$$

Therefore, regarding user's $i$ load, we can define a feasible scheduling set $X_i$ that is:

$$X_i = \left\{x_i \middle| \underline{E_i} \le \sum_{k=t_i^s}^{k=t_i^l} x_i^k \le \widetilde{E}_i, \right.$$

$$\underline{x_i^k} \le x_i^k \le \widetilde{E}_i, \forall k \in \left[t_i^s, t_{i,d}^l\right] \tag{12}$$

$$x_i^k = 0, \quad \forall k \in \boldsymbol{H} \backslash \left[t_i^s, t_i^l\right]$$

We assume that each user $i$ is fully satisfied when her load consumes cumulative energy equal to $\widetilde{E}_i$. The overall utility that she obtains from her load's operation depends on its total energy consumption over the entire scheduling period. Therefore, we adopt a quadratic utility function as Samadi et al. (2012) that is mathematically expressed as follows:

$$U_i = U_{\max,i} - \delta_i * \left(\widetilde{E}_i - \sum_{k=t_i^s}^{k=t_i^l} x_i^k\right)^2 \tag{13}$$

Without loss of generality, in order for $U_i(0) = 0$, we set $U_{\max,1} = \delta_i * \widetilde{E}_i$. Each user declares how much she values the energy consumed by her load through parameter $\delta_i$. Higher values of $\delta_i$ mean higher utility value, i.e., less flexibility.

Finally, it is highlighted that the aforementioned utility functions do not constitute novelty of this work. On the contrary, they are widely adopted for the evaluation of pricing schemes (Samadi et al. 2012; Ma et al. 2014; Zhang et al. 2014). The proposed pricing schemes are open to various types of users and cost models.

## Problem formulation and proposed algorithm

In this section, we present the method that ESP uses in order to calculate the vector of prices $\rho$. Additionally, in order to model the problems of scheduling the operation of ESS and the consumption of users, we formulate a bi-level optimization problem. In the upper level, ESP minimizes its energy cost, while in the lower level each user maximizes her welfare according to her preferences (utility function) and the prices set by the ESP.

Without harm of generality, the objective of the ESP is to minimize its energy cost by optimally operating ESS. ESP receives the users' energy schedules $\boldsymbol{x_i}$ and calculates the ESS charging/discharging schedule by solving the following optimization problem:

$$\min_r \left\{\sum_{k=1}^{T} \left(C\left(g^k\right)\right)\right\} \tag{14}$$

Subject to (1), (2), (3), (4), (5).

In this case, Eqs. (1) and (3) express physical constraints that ESS sets. Additionally, in order to avoid

having an energy surplus or deficit during the scheduling horizon $H$ and to take into consideration the requirements of the following scheduling horizon, we impose the constraint which presented in Eq. (2). Alternatively, we could set $S^{T+1}$ to be larger than a minimum value. Additionally, constraint in Eq. (5) expresses that (i) in the case of ESS charging, the energy drawn from the main grid is equal to the energy charged to the ESS plus the energy demand, and (ii) in the case of ESS discharging, the energy drawn from the grid plus the energy that ESS provides is equal to total demand. Thus, we have a typical convex optimization problem that can be solved according to Bertsekas (2015) and/or Boyd and Vandenberghe (2004).

The question that is answered in the remainder of this section is how ESP will put in the bills of its customers the cost of energy that is charged to or discharged from the ESS in a fair way in order to avoid harming the motivation for users' DR actions. The approach applied throughout the literature is captured in Eq. (15). Users are billed with the total energy cost of the ESP in each time slot $k$. The problem with this approach is that the cost of charging the ESS at time $k$ is paid by the users who happen to consume at that time slot (off-peak hours). Therefore, the users that consume during peak hours (when the ESS discharges) get a discount on their price, at the expense of the former users.

$$\rho^k = \frac{C(g^k)}{x^k} \tag{15}$$

In order to achieve a fair ESS-aware RTP scheme, we denote as $V^k$ the sunk cost of the energy that is stored in ESS at the beginning of time interval $k$. In other words, $V^k$ represents the cost that ESP has paid to the wholesale market in order to buy and store energy. Thus, in time instant $k$ ESP disposes in its ESS $\sum_{j=0}^{k} r^k$ energy units. Then, we can calculate $V^{k+1}$ as a function of $V^k$ through Eqs. 16 and 17.

$$V^{k+1} = V^k + C(g^k) - C(x^k), \quad \text{if} \quad r^k \geq 0 \tag{16}$$

$$V^{k+1} = Vk * \left(1 + \frac{r^k}{S^k}\right), \quad \text{if} \quad r^k < 0 \tag{17}$$

According to Eq. (16), in the case of ESS charging during interval $k$, $V^{k+1}$ (which is the value of energy that is stored in ESS at the beginning of time instant $k+1$) is increased from $V^k$ (which is the value of energy that is stored in ESS at the beginning of time instant $k$) by an amount equal to the cost of the total energy drawn from the main grid (second term of the sum in Eq. (16)) minus the cost of energy drawn to cover the total users' demand during time slot $k$ (third term of the sum in Eq. (16)).

In the case of ESS discharging, $V^{k+1}$ is lower than $V^k$, which is decreased by a factor that is equal to the fraction of the ESS energy that is discharged as depicted in Eq. (17). In more detail, in Eq. (17), the multiplicand of $V^k$ (value of energy in ESS at the beginning of time $k$) is equal with the ratio between the energy remaining in ESS after the discharge and the energy in ESS before the discharge ($S^k$).

Through the use of the sunk cost of stored energy, we are able to determine the real-time energy price $\rho^k$, i.e., the price per unit of energy consumption at time slot $k$, as

$$\rho^k = \frac{C(x^k)}{x^k}, \quad \text{if} \quad r^k \geq 0 \tag{18}$$

$$\rho^k = \frac{[C(x^k) + V^k - V^{k+1}]}{x^k}, \quad \text{if} \quad r^k < 0 \tag{19}$$

A user $i$, as a response to price signal $\rho$, adapts her consumption according to her preferences. Each user's objective is to maximize her total utility minus her electricity bill, or in other words her *Welfare*. Thus, each user $i \in \boldsymbol{N}$ receives the price vector $\rho$ from the ESP and calculates her energy schedule $x_i$ by solving the following optimization problem:

$$\max_{\boldsymbol{x_i}} \left\{ U_i(\boldsymbol{x_i}) - \sum_{k=1}^{T} \left(\rho k * x_i^k\right) \right\} \tag{20}$$

In the above optimization problem, solution $x_i^*$ should satisfy either Eq. (9) in case users own loads of "type A," or Eq. (12) in case users operate loads of "type B."

Customers (end users) and ESP exchange messages, as in every real-time pricing architecture (e.g., Samadi et al. 2010; Zhang et al. 2014), until the convergence of the system to the optimal price vector and energy schedule of the participating users. The proposed algorithm is noted as F-RTP-S and it is summarized in Table 2. In Tables 2, 3, and 4, index $j$ expresses the iteration of the algorithm and the term *desired accuracy* expresses the condition of the termination of the algorithm. Finally,

**Table 2** Proposed algorithm for the price and the energy consumption calculation in *F-RTP-S*

| Algorithm 1 (F-RTP-S) |
|---|
| 1 Initialization: set $j=1$, $x_i^{k,j}=\widetilde{x}_i^k$, $r^{k,j}=0$, $\rho^{k,j}=\frac{C\left(\sum_{i=1}^N x_i^{k,j}\right)}{\sum_{i=1}^N x_i^{k,j}}$ $\forall i\in N$, $k\in H$ |
| 2 Repeat |
| 3 for each user $i\in N$ |
| 4 Calculate $x_i^{k,j}$, $\forall k\in H$ by solving (20) |
| 5 Update $\rho^{k,j}$, $\forall k\in H$ using (16),(17),(18),(19) |
| 6 end for |
| 7 Calculate $r^{k,j}$ $\forall k\in H$ by solving (14) |
| 8 Calculate *divergence* = $\max\left\lvert x_i^{k,j+1}-x_i^{k,j}\right\rvert$ $\forall i\in N$, $k\in H$ |
| 9 Until *divergence* < *desired accuracy* |
| 10 End |

the Appendix presents the proof of the convergence of F-RTP-S algorithm.

In order to compare the proposed F-RTP-S (with respect to the requirements that we analyzed in the introduction), we also implemented RTP as analyzed in Li et al. (2011) in case that there is no ESS at all. In this case (*RTP*), the price $\rho^k$ is calculated from Eq. (15) and the pricing algorithm is summarized in Table 3.

Additionally, in order to compare *F-RTP-S*, we put RTP in cases that there is an ESS (*RTP-S*) but without using Eqs. (16)–(19) which preserve fairness to RTP in case that there is ESS. In this case, the price $\rho^k$ is calculated from Eq. (15) and the algorithm is summarized in Table 4. Pease note that in this case, the problem is that the cost of charging the ESS at time $k$ is paid by the users who happen to consume at that time slot and not by those who actually consume the ESS discharging energy.

Finally, we consider the case where ESP optimally schedules the function of a shared ESS; however, users are not motivated to alter their consumption pattern (as in *RTP*, *RTP-S*, *F-RTP-S*) and thus, they consume electricity according to their desired energy schedules. This is noted as (*S*). In other words, in this case, there is no DR program and $x_i^k=\widetilde{x}_i^k$. In this case, the $\rho^k$ is calculated again from Eq. (15) as in RTP but the consumption of each user is a priory set (price independent). This algorithm is summarized in Table 5.

Intuitively, the advantage of F-RTP-S over RTP-S is that the cost of charging the ESS with $r^k$ at time slot $k$ is

**Table 3** Algorithm for the price and the energy consumption calculation in *RTP*

| Algorithm 2 (RTP) |
|---|
| 1 Initialization: set $j=1$, $x_i^{k,j}=\widetilde{x}_i^k$,, $\rho^{k,j}=\frac{C\left(\sum_{i=1}^N x_i^{k,j}\right)}{\sum_{i=1}^N x_i^{k,j}}$ $\forall i\in N$, $k\in H$ |
| 2 Repeat |
| 3 for each user $i\in N$ |
| 4 Calculate $x_i^{k,j}$, $\forall k\in H$ by solving (20) |
| 5 Update $\rho^{k,j}$, $\forall k\in H$ using (15) |
| 6 end for |
| 7 Calculate *divergence* = $\max\left\lvert x_i^{k,j+1}-x_i^{k,j}\right\rvert$ $\forall i\in N$, $k\in H$ |
| 8 Until *divergence* < *desired accuracy* |
| 9 End |

**Table 4** Algorithm for the price and the energy consumption calculation in *RTP-S*

| Algorithm 2 (RTP-S) |
|---|
| 1 Initialization: set $j=1$, $x_i^{k,j}=\widetilde{x}_i^k$, $r^{k,j}=0$, $\rho^{k,j}=\frac{C\left(\sum_{i=1}^N x_i^{k,j}\right)}{\sum_{i=1}^N x_i^{k,j}}$ $\forall i\in N$, $k\in H$ |
| 2 Repeat |
| 3 for each user $i\in N$ |
| 4 Calculate $x_i^{k,j}$, $\forall k\in H$ by solving (20) |
| 5 Update $\rho^{k,j}$, $\forall k\in H$ using (15) |
| 6 end for |
| 7 Calculate $r^k$, $\forall k\in H$ by solving (14) |
| 8 Calculate *divergence* = $\max\left\lvert x_i^{k,j+1}-x_i^{k,j}\right\rvert$ $\forall i\in N$, $k\in H$ |
| 9 Until *divergence* < *desired accuracy* |
| 10 End |

**Table 5** Algorithm for the price calculation in *S*

| Algorithm 4 (S) |
|---|
| 1 Initialization: set $x_i^k=\widetilde{x}_i^k$, $r^k=0$, $\forall i\in N$, $k\in H$ |
| 2 Calculate $r^k$, $\forall k\in H$ by solving (14) |
| 3 Calculate $\rho^k$, $\forall k\in H$ by solving (15) |

not paid by the users that happen to consume in $k$, but by the users that actually consume this amount of energy at a later time slot $k' > k$. Finally, Table 6 below summarizes the features of the four pricing algorithms that we present above.

## Performance evaluation

In this section, we set up a simulation testbed in order to illustrate the performance of the proposed pricing model (*F-RTP-S*) and we present the results of the simulations that we conducted. We consider a system of an ESP and $N = 50$ users, each of them operating one flexible load that desirably consumes an energy amount $\widetilde{E}_i \in [4, 30]$ kWh. Without loss of generality, we set $x_i^k - = 0$ for each user $i$ at every timeslot $k$. The desired operation time schedules of users' loads ($H_{s,\ i}, \forall\, i \in N$) vary through the scheduling period and the aggregate electricity consumption curve of the system's flexible loads is depicted in Fig. 3. We consider an average flexibility case, in which users are neither reluctant to change their consumption pattern, nor highly enthusiastic to do so. We select the parameters of utility functions (Eqs. (7) and (13)) accordingly. The scheduling period consists of $T = 24$ timeslots of equal duration of 1 h. Energy cost function parameter $c$ (Eq. (6)) is set to 0.02 and ESP profit percentage ($\pi$) is set to 0.20. Finally, as far as the ESS parameters are concerned, we set $S_{\max} = B$, $S_{\min} = 0.2{*}B$, $S_I = 0.5{*}S_{\max}$, $\eta_c$ and $\eta_d$ to 1. We are aware that the ESS cost increases with $B$ and this factor affects the decision of the ESP concerning the size of ESS that it will install. However, storage sizing is out of the scope of this work and this problem will be addressed in a future study.

As we discussed earlier, in order to derive a comparative study, we consider the following four cases:

- Case 1 (*RTP*): RTP scheme with no ESS installed.
  A set of users is served by a single ESP. The participants decide their consumption schedule by maximizing their welfare and taking into consideration the price that ESP sets.
- Case 2 (*S*): A shared ESS is installed in the premises of ESP while users do not participate in a DR scheme (i.e., there is no RTP).
  ESP utilizes the shared ESS in order to minimize its energy cost. Users' consumption schedule is their desired regardless the energy cost.
- Case 3 (*RTP-S*): A shared ESS is installed in the premises of the ESP and an RTP scheme is implemented.
  Users solve the same optimization problem as in case 1. ESP makes use of the ESS, in order to further reduce the energy cost. In every time slot, customers are billed with the cost of the total energy that is produced and not with the energy that is intended to cover their demand (i.e., unfair pricing scheme).
- Case 4 (*F-RTP-S*): The proposed pricing model, in which the ESP fairly allocates its energy costs among the time slots (i.e., in every timeslot, consumers pay for the energy they consume and not for the total energy that ESP purchases, part of which is used to charge the ESS). Furthermore, in this section, it is shown that our proposed pricing model also fairly allocates the ESP's costs among its clients (see Figs. 10 and 14).

**Table 6** Pricing schemes and available features

| Feature/pricing scheme | DR | ESS | Fair ESS billing across time |
|---|---|---|---|
| RTP | Yes | No | No |
| S | No | Yes | No |
| RTP-S | Yes | Yes | No |
| F-RTP-S | Yes | Yes | Yes |

For evaluation purposes, we define the following key performance indicators (KPIs):

1. Energy cost ($G$): The cost that ESP has to pay in order to purchase the energy that needs to cover the energy demands of its customers

$$G = \sum_{k=1}^{T} C\left(g^k\right) \tag{21}$$

2. Total welfare ($TW$): The summation of the aggregate users' welfare and ESP profits

$$TW = AUW + EP \tag{22}$$

Where,

$$\mathrm{AUW} = \sum_{i=1}^{N} U_i - \sum_{i=1}^{N}\sum_{k=1}^{T}\left(\rho k * x_i^k\right) \tag{23}$$

and

$$\mathrm{EP} = \sum_{i=1}^{N}\sum_{k=1}^{T}\left(\rho k * x_i^k\right) - \sum_{k=1}^{T} C\left(g^k\right) \tag{24}$$

3. Time fairness at time interval $k$ ($TF(k)$) is a KPI that expresses the ratio between the cost of the energy that is consumed at time interval $k$ and the income of the ESP at the same time interval $k$. For clarity (demonstration purposes), in this ratio, we subtract one in order to have zero as the desired value of $TF(k)$

$$TF(k) = \left| \frac{C(g^k)}{\rho k * \sum_{i=1}^{N} x_i^k} - 1 \right|, \quad \forall k \in \boldsymbol{H} \tag{25}$$

4. Fairness of user $i$ ($UF(i)$) is a KPI that expresses the way that ESS's added value is distributed in a fair way among all the participating users

$$UF(i) = \frac{|UB_i - UFB_i|}{UFB_i}, \forall i \in \boldsymbol{N} \tag{26}$$

Where the bill that each user $i$ pays is:

$$UB_i = \sum_{k=1}^{T} \left( \rho k * x_i^k \right), \forall i \in N \tag{27}$$

$UFB_i$ is the bill that user $i$ must pay in a fair system and is determined from the subtraction between the bill that user $i$ would pay in case of no ESS and the benefit (added value) that ESS brings divided by the number of users. In Eqs. (28), (29), (30), (31), and (32), the fair bill of user $i$ is defined.

$$\mathrm{UFB}_{\boldsymbol{i}} = \mathrm{UB}_{\boldsymbol{o},\boldsymbol{i}} - \frac{SB}{N}, \forall i \in N \tag{28}$$

Where,

$$\mathrm{UB}_{o,i} = \sum_{k=1}^{T} \rho_{RTP}^k * x_{i,RTP}^k, \forall i \in \boldsymbol{N} \tag{29}$$

$$\mathrm{SB} = \mathrm{SoD} - \mathrm{CoC} \tag{30}$$

Where,

$\rho_{RTP}^k$ The price that ESP sets in time slot $k$ in case 1 (RTP with no ESS)

$x_{i,RTP}^k$ Energy consumption of user $i$ in time slot k in case 1

$$\mathrm{CoC} = \sum_{k\_ch} \left( C\left(g^{k\_ch}\right) - C\left(\sum_{k\_ch} x^{k\_ch}\right) \right) \tag{31}$$

$$\mathrm{SoD} = \sum_{k\_dis} \left( C\left(\sum_{k\_dis} x^{k\_dis}\right) - C\left(g^{k\_dis}\right) \right) \tag{32}$$

In Eq. (31), $g^{k\_ch}$ denotes the energy that ESP purchases in the wholesale market at time instants when the ESS is charged and $x^{k\_ch}$ denotes the total users' consumption in the same time intervals. In Eq. (32), $x^{k\_dis}$ denotes the total users' demand in time intervals when the ESS is discharged, while $g^{k\_dis}$ denotes the energy that is purchased in the wholesale energy market by the ESP during these time slots.

Users own loads of "type a"

In this scenario, $\omega_i$ (Eq. (7)) is uniformly selected for each consumer $i$ and every timeslot $k$ within the interval

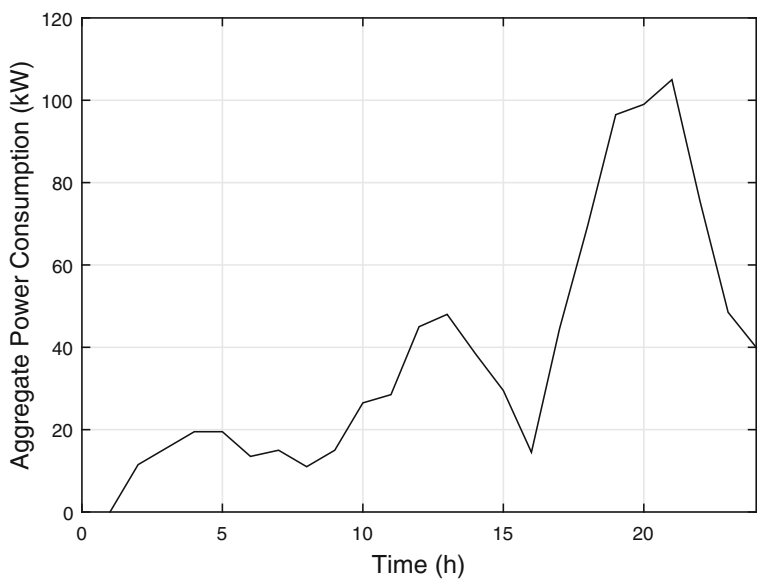



**Fig. 3** Users' desired aggregate energy consumption curve

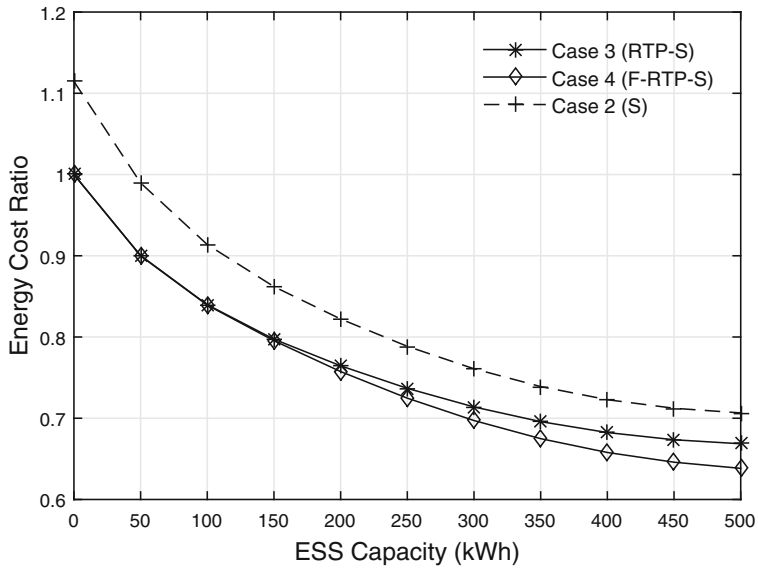



**Fig. 4** Energy cost ratio of cases 2, 3, and 4 (S, RTP-S, F-RTP-S) as a function of ESS capacity ($B$)

[1, 5]. In order to compare the four algorithms in terms of energy cost ($G$) and total welfare (TW), we introduce the terms energy cost ratio and total welfare ratio:

$$\text{Energy cost ratio} = \frac{\text{energy cost in case m}}{\text{energy cost in case 1}},\ m \in [2,3,4] \quad (33)$$

$$\text{Total welfare ratio} = \frac{\text{total welfare in case m}}{\text{total welfare in case 1}},\ m \in [2,3,4] \quad (34)$$

Figure 4 depicts the energy cost ratio of all three algorithms that utility an ESS. An RTP scheme implementation (case 1—*RTP*) manages an 10% reduction in the energy cost ($G$) in comparison with a conventional energy retail market, in which users simply consume their desired energy demand without participating in a DR program (energy cost in case 2 with $B = 0$ is larger than energy cost in case 1 by 11.5%). We highlight here that this reduction highly depends on users' flexibility. The energy cost reduction could be larger in case of higher flexibility, but it could also be negligible in the case of inelastic users' demand. In order to achieve smaller energy ESP costs, an alternative to RTP is the installment of a shared ESS (cases 2, 3, and 4). In this case, the energy cost reduction increases with the ESS

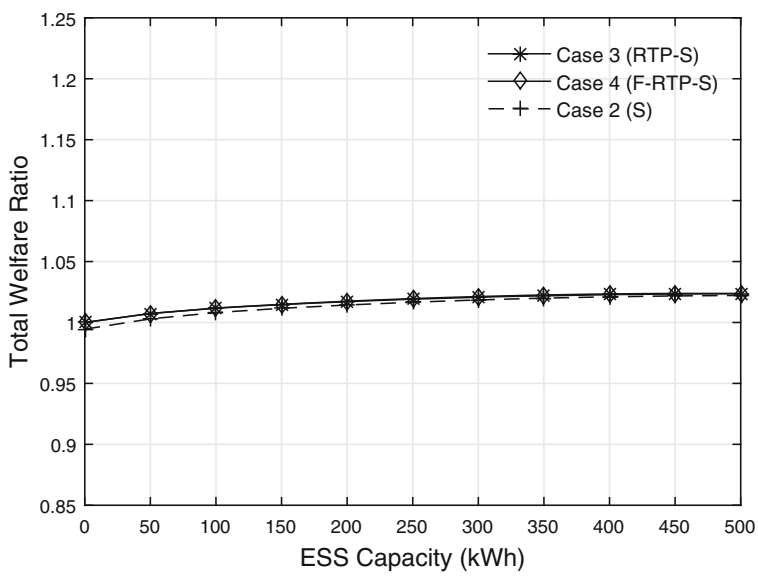



**Fig. 5** Total welfare ratio of cases 2, 3, and 4 (S, RTP-S, F-RTP-S) as a function of ESS capacity ($B$)

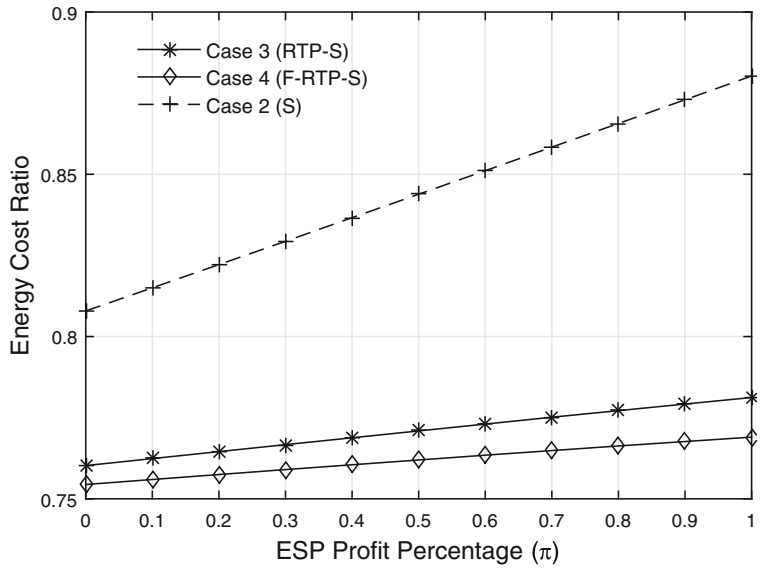



**Fig. 6** Energy cost ratio of cases 2, 3, and 4 (S, RTP-S, F-RTP-S) as a function of ESP profit percentage ($\pi$)

capacity. The utilization of an ESS alone (without a DR program implementation) can reduce the energy cost up to 30% ($B = 500$ kWh) more than what RTP alone can do. In this paper, we propose a RTP scheme combined with the installment of a shared ESS, which as we can see in Fig. 4, achieves even better results, as cases 3 and 4 (RTP-S and F-RTP-S) reduce the ESP's energy cost by 33 and 36% respectively in comparison with Case 1.

In Fig. 5, total welfare ratio is depicted. We observe that a shared ESS deployment reduces the total energy cost without diminishing social welfare. On the contrary, an ESS installation can marginally increase TW by up to 2.4%.

In order to prove that the superiority of the proposed pricing model is independent from the market conditions (profit percentage $\pi$), we present the following two figures. In Fig. 6, the energy cost ratio in each of the three algorithms that include an ESS operation as a function of the ESP profit percentage ($\pi$) is depicted. We observe that an ESS of sufficient capacity ($B =$ 200 kWh) achieves lower energy cost ($G$) regardless of the value of $\pi$ that ESP selects. Figure 7, which

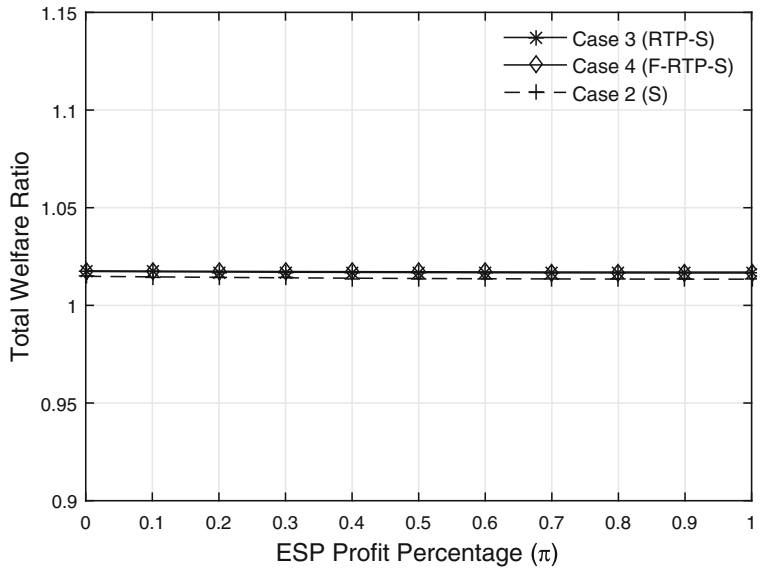



**Fig. 7** Total welfare ratio of cases 2, 3, and 4 (S, RTP-S, F-RTP-S) as a function of ESP profit percentage ($\pi$)

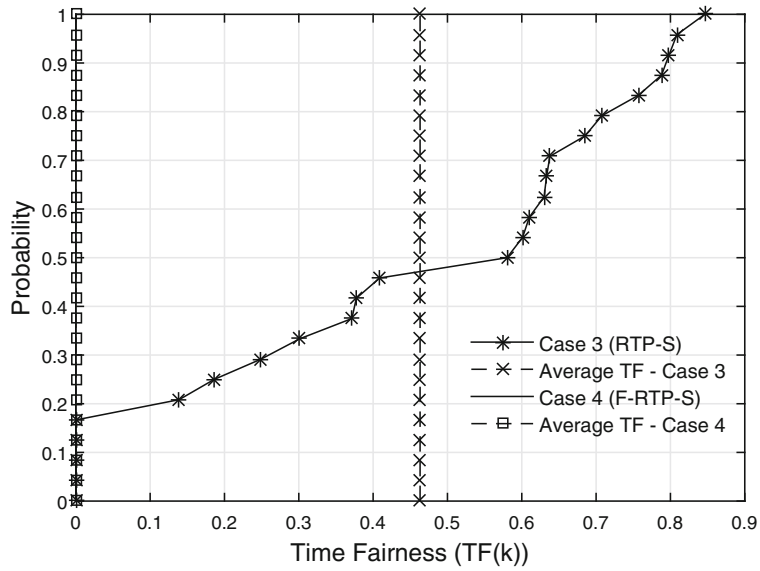



**Fig. 8** CDF of TF ($k$) in cases 3 and 4 (RTP-S, F-RTP-S). $B$ = 200 kWh

depicts the total welfare ratio as a function of the ESP profit percentage ($\pi$), ensures that the energy cost reduction comes with no TW decrease.

Figures 8 and 9 depict the cumulative distribution function (CDF) of TF ($k$). As analyzed in the beginning of this section, $TF$ ($k$) is a KPI that indicates whether the ESP's income in each time interval reflects the electricity's cost (how "fair" is the pricing in each time slot $k$). Our proposed F-RTP-S is the fairest possible. As we observe in Fig. 8 ($B$ = 200 kWh), in the case of *RTP-S*, there is a wide distribution of $TF$ ($k$) in various time slots around the average $TF$ ($k$). RTP-S is less fair than F-RTP-S by 46% on average. This gap increases with ESS capacity as we can see in Fig. 9, where ESS capacity is set to 300 kWh and F-RTP-S is fairer than RTP-S by 66% on average.

The installment of a shared ESS should be equally beneficial for every user $i$ among the ESP's customers. Ideally, users' bills should be equal to what they would pay in case 1 (RTP) minus their ESS benefit dividend, which is:

$$\mathrm{SBD}_i = \frac{SB}{N}, \forall i \in N \tag{35}$$

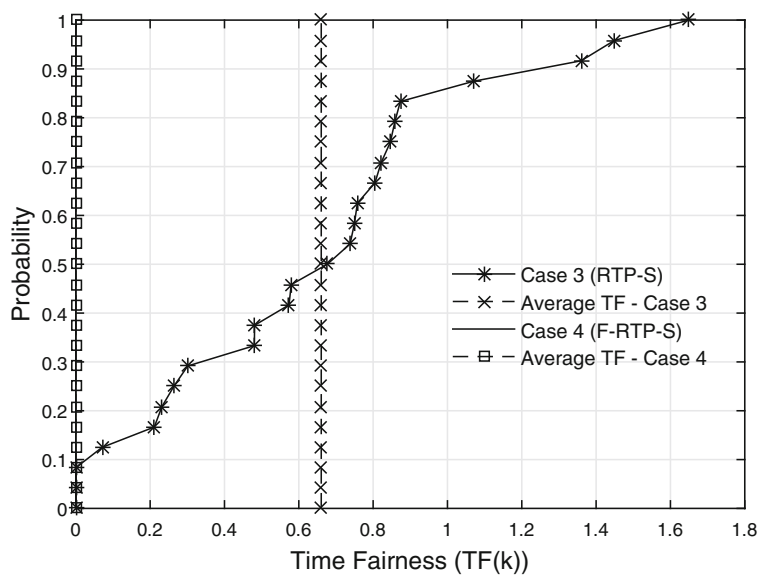



**Fig. 9** CDF of $TF$ ($k$) in cases 3 and 4 (RTP-S, F-RTP-S). $B$ = 300 kWh

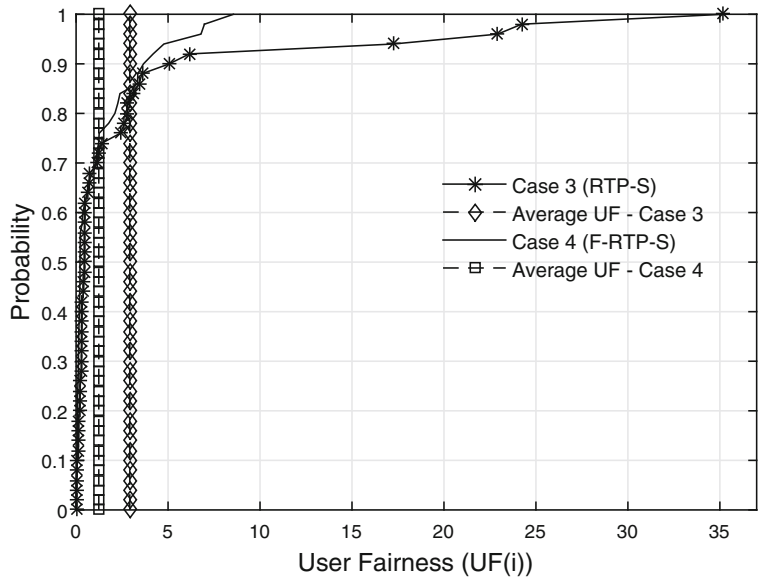



**Fig. 10** CDF of *UF* (*i*) in cases 3 and 4 (RTP-S, F-RTP-S). *B* = 200 kWh

In order to assess this, we have introduced in the beginning of this section *UF* (*i*) as a KPI. We intend to prove that in *F-RTP-S*, users' bill vector is closer to the ideal one (which is zero as derived from Eq. (26)), than in *RTP-S*. Thus, in Fig. 10, we present the CDF of UF (*i*) for RTP-S and F-RTP-S cases. As we can observe, the CDF of F-RTP-S and the average value of UF (*i*) in F-RTP-S are much closer to zero (desired value) than the CDF of RTP-S and the average value of UF (*i*) in *RTP-S*. This fact indicates that the benefits that an ESS installment provides are *more fairly* distributed when F-RTP-S is applied. This is explained by the fact that, in case RTP-S scheme is implemented, users who consume energy at times when the ESS is charged, they pay the whole ESS charging cost, while users who consume energy at ESS discharge time slots reap the total ESS benefit. On the contrary, the F-RTP-S scheme implementation is fairer toward the users, since they pay what they actually consume.

Users own loads of "type B"

In this scenario, $\delta_i$ is randomly selected within the interval [1, 5] in order to consider users of medium

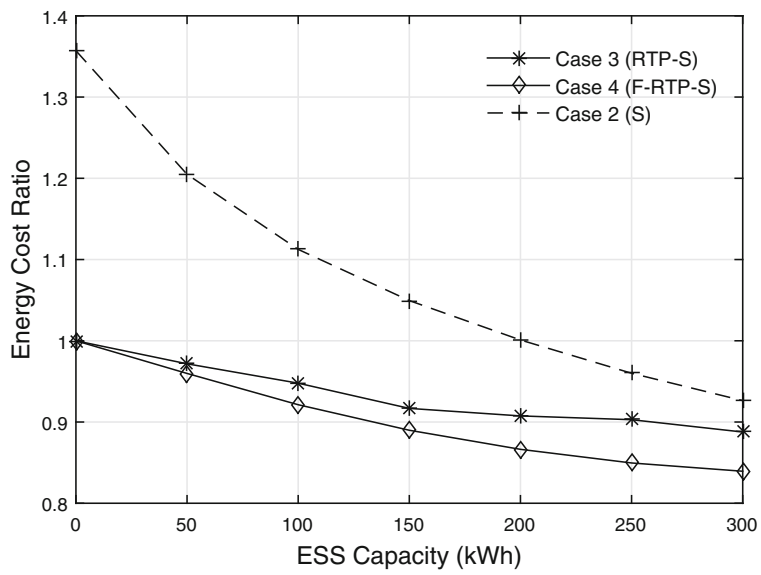



**Fig. 11** Energy Cost ratio of cases 2, 3, and 4 (S, RTP-S, F-RTP-S) as a function of ESS capacity (*B*)

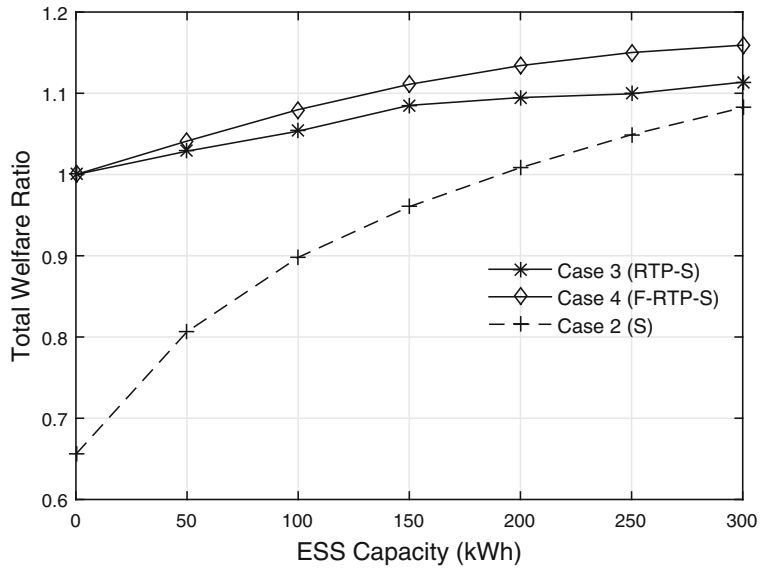



**Fig. 12** Total welfare ratio of cases 2, 3, 4 (S, RTP-S, F-RTP-S) as a function of ESS capacity ($B$)

flexibility. Additionally, we consider that each consumer $i$ sets her earliest and latest load operating times one to three hours before and after $\widetilde{H_{s,i}}$. Also, we set $E_{i-} = 0$.

In Fig. 11, the energy cost ratio of all three algorithms that utilize an ESS is depicted. The RTP scheme implementation reduces energy cost by 26% in comparison with the base case in which users consume their desired energy demand in lack of any DR program (energy cost in case 2 with $B = 0$ is larger than energy cost in case 1 by 35.7%). In order for algorithm (S) to achieve better results than algorithm (RTP), the installation of an ESS of capacity more than 200 kWh is necessary. Eventually, for $B = 300$ kWh, algorithm (S) manages a 7.5% larger cost reduction than algorithm (RTP). The combination of RTP implementation and an ESS installment provides ESP with the capability to further decrease its energy cost. More specifically, algorithm (RTP-S) accomplishes a larger cost reduction than RTP by 11.2%, while F-RTP-S is even more efficient as it reduces energy cost by 16% more than RTP. In Fig. 12, we can see that both RTP-S and F-RTP-S are efficient in reducing energy cost, while they increase TW comparing to RTP (case 1). In fact, algorithm (RTP-S) implementation results in a higher TW than RTP by 11.4%, while F-RTP-S is even

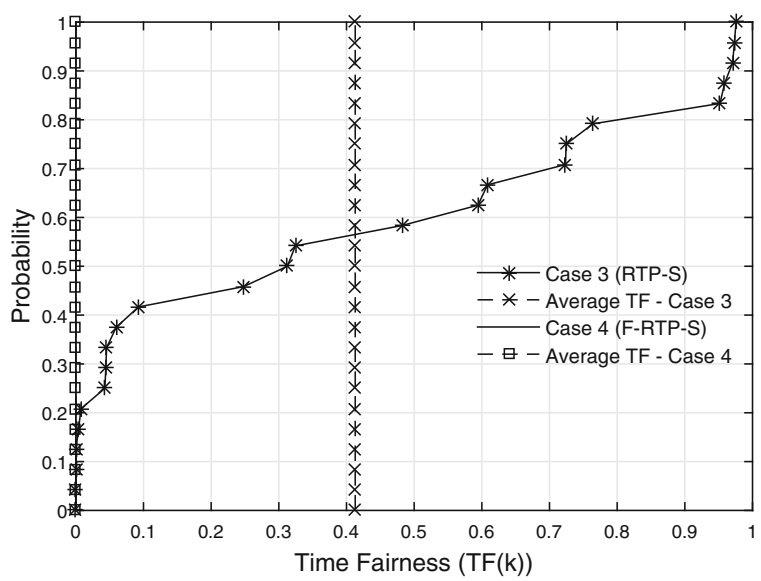



**Fig. 13** CDF of $TF(k)$ in cases 3 and 4 (RTP-S, F-RTP-S). $B =$ 200 kWh

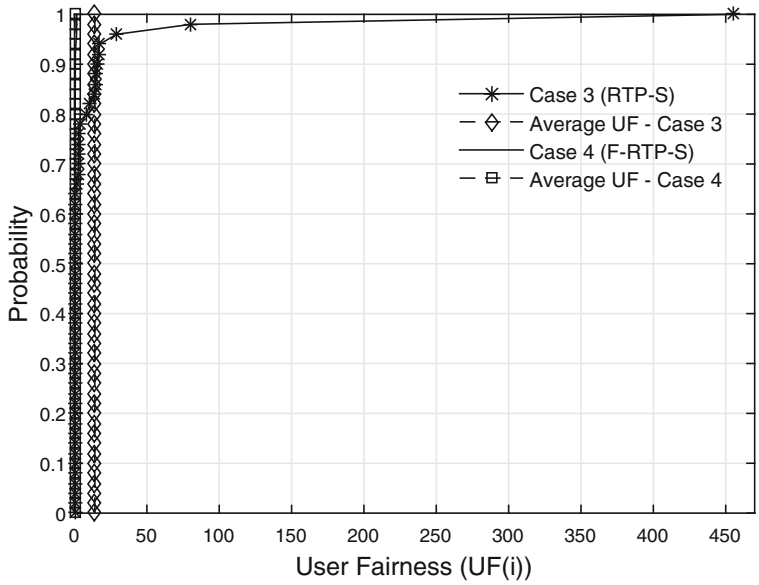



**Fig. 14** CDF of *UF* (*i*) in cases 3 and 4 (RTP-S, F-RTP-S). $B = 200$ kWh

more effective as it achieves a 16% increase in TW comparing to RTP.

Figure 13 demonstrates that RTP-S is less fair than F-RTP-S by 41.3% in terms of TF (k) on average when ESP installs an ESS of capacity $B = 200$kWh. Figure 14 demonstrates a huge discrepancy in terms of *UF* (*i*) on average between F-RTP-S and RTP-S, as in F-RTP-S users' average bill differs from $UFB_i$ by 26%, while the equivalent percentage in RTP-S is 1400%. This is explained by the fact that there are consumers, who should pay near to zero bills (according to $UFB_i$); however, in RTP-S, they still pay a normal electricity bill. Hence, F-RTP-S is greatly fairer than RTP-S on average regarding the billing of consumers.

## Conclusions and future work

Energy storage systems are becoming a substantial component of the Smart Grid as they facilitate ESPs and the consumers in various ways. Due to the high costs of ESS technologies, it is reasonable to assume that a progressive utility company would deploy a shared ESS. In this paper, we proposed a RTP scheme adopted by an ESP, which also leverages a shared ESS in order to further minimize its energy costs. As a future work, we intend to extend the results of this paper to more advanced system models that include renewable energy generating units, more advance DSM strategies, sophisticated ESS degradation and depreciation cost models. Moreover, ESS sizing algorithms in conjunction with different pricing models need to be studied, in order for the ESP to optimally design its business strategy.

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**Compliance with ethical standards**

**Conflict of interest** The authors declare that they have no conflict of interest.

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