Optimality and PAR Reduction in Autonomous Demand Response: Evaluation and Billing Mechanisms

ABASSI Abdelfattah [1,*], and *ARID Ahmed* [2,*], *and* BENAZZA Hussain[3,*]

[1]Mouly Ismail University, ENSAM, MEKNES MOROCCO

[2] Moulay Ismail University, ENSAM, MEKNES MOROCCO

[3] Moulay Ismail University, ENSAM, MEKNES MOROCCO

Abstract. The main objective of this paper is to propose a more efficient, distributed, and multi-objective billing model that can be implemented in every smart meter in the grid for achieving optimality and fairness. First, we develop a new evaluation index to evaluate such as billing model not only in addressing fairness but also to minimize the cost and reduce the Peak-to-Average Ratio (PAR) in the load demand and subsequently the bill of each customer. Then, we study some of the billing models that exist in the literature and evaluate them with our evaluation index. Simulations are performed to test the performance of our model in terms of optimality, PAR reduction and fairness.

1 INTRODUCTION

The concept of Demand-Side Management (DSM) includes energy saving actions developed on the side of the final consumer, not the energy producer [1]. One of the most used techniques in DSM is Demand Response (DR) programs. In DR programs, the company can control directly and remotely the energy consumption of some machines like air-conditioner and water heater. This approach in DR is Direct Load Control (DLC) [2]. Other models encourage users to reduce their energy consumption during peak hours. These models generally give each participating user a discount on their overall bill [3]. The installation of smart meters allows users to control and visualize their energy consumption in real time and become participants in DR program as suggested in [4].

The discussions and analyses in this paper are based on the results presented in [4] and [5]. First, we study two billing models presented in [4], [6], [7] and explain in detail the main features of each model to achieve optimality and fairness in the system. The main contribution of this paper is to present a new evaluation index that allows to evaluate the performance of a billing system in terms of cost optimization in the system and PAR reduction, as well as fairness. Then a new billing model will be developed that allow the production company to bill its customers in a distributed manner, thus guaranteeing optimality and fairness. Finally, we show via simulation the performance of our billing model.

The rest of this paper is organized as follows. System model will be presented in Section 2. In Section 3 we will present the two ways to achieve optimality in the system. Section 5.1 presents a new index to evaluate such a billing model in terms of fairness, optimality, and PAR reduction. Our billing model will be presented in Section 5.2. The simulations results will be given in Section 6. The paper is concluded in Section 7. This is an abridged version of the full paper.

2 SYSTEM MODEL

Consider a smart power grid with a set of $\mathcal{N} = \{1, \ldots, N\}$ users that share an energy source. For one day, the time is divided into fixed and equal time slots $\mathcal{H} = \{1, \ldots, H\}$. For example, time slot may take one hour, and we have $H = 24$. Let $\mathcal{H}_n = \{\alpha_n, \ldots, \beta_n\}$, where $\alpha_n \in \mathcal{H}$ is the start time slot and $\beta_n \in \mathcal{H}$ is the end time slot of nth user. The cost of electricity in each time slot in the grid is calculated by the company using a generation cost function C_h. Let $L_h > 0$ denote the total load in the system at time slot $h \in \mathcal{H}$. As an example of generation cost function, we may use [8]:

$$C_h(L_h) = a_h L_h^2 + b_h L_h + c_h, \tag{1}$$

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where $a_h > 0$ and $b_h, c_h \geq 0$ at each hour $h \in \mathcal{H}$.
Let $x_n^h \in \mathbb{R}^+$ for $h = 1, \ldots, H$ denote user n's load at hour h and E_n user n's total load. We define user n's load scheduling vector as:

$$\mathbf{x_n} = [x_n^1, x_n^2, \ldots, x_n^H], E_n = \sum_{h=1}^{H} x_n^h \text{ and } E_T = \sum_{i=1}^{N} E_i \tag{2}$$

In this regard, we can define a feasible energy consumption scheduling set corresponding to user n as follows [9]:

* Corresponding author: abassi.mri@gmail.com

$$\mathcal{X}_n = \left\{ \mathbf{x_n} | \sum_{h=\alpha_n}^{\beta_n} x_n^h = E_n; x_n^h = 0, \forall h \in \mathcal{H} \setminus \mathcal{H}_n \right\} \quad (3)$$

The PAR in load demand is:

$$PAR = \frac{H \max_{h \in \mathcal{H}}(L_h)}{\sum_{h \in \mathcal{H}} L_h}. \quad (4)$$

3 ACHIEVING OPTIMALITY

In the centralized case, the optimal cost in the system is obtained by solving the following optimization problem using convex programming techniques [10]:

$$C_{\mathcal{N}}^* = \min_{\{x_n \in \mathcal{X}_n\}} \sum_{h=1}^{H} C_h \left(\sum_{n \in \mathcal{N}} x_n^h \right). \quad (5)$$

In decentralized fashion, the authors in formulate the problem as an energy consumption Game 1 among users:

- Players: Registered users in set $\mathcal{N}$.
- Strategies: Each user $n \in \mathcal{N}$ selects its energy consumption scheduling vector $\mathbf{x_n}$ to maximize its payoff.
- Payoffs $P_n(\mathbf{x_n}, \mathbf{x_{-n}})$ for each user $n \in \mathcal{N}$ where $P_n(\mathbf{x_n}, \mathbf{x_{-n}}) = -b_n$. Here, $\mathbf{x_{-n}} = [\mathbf{x_1}, \dots, \mathbf{x_{n-1}}, \mathbf{x_{n+1}}, \dots, \mathbf{x_N}]$ denotes the vector containing the energy consumption schedules and b_n is the bill of user n.

4 EXAMPLES OF BILLING MODELS

We consider billing mechanism used in [4] denoted by B_n and billing mechanism in [9] denoted by $\widetilde{B_n}$. Assume that $N = 3$ users share an energy source and $E_1 = E_2 = 10$ kWh and $E_3 = 12.5$ kWh, $\alpha_1 = \beta_1 = 1$, $\alpha_2 = 1, \beta_2 = 2$ and $\alpha_3 = 1, \beta_3 = 4$. The users want to schedule their load for the next $H = 4$ hours. With this paradigm, the authors in [4] propose an algorithm to be implemented to find the Nash Equilibrium (NE) of Game 1. According to the billing scheme B_n and $\widetilde{B_n}$, the NE for both billings is shown in Table 1 and Table 2 respectively.

Table 1. THA NASH EQUILIBRIUM WHEN BILLING IS $\widetilde{B_n}$.

$user$	x_n^1	x_n^2	x_n^3	x_n^4	B_n
1	10	0	0	0	17.49
2	0	10	0	0	17.49
3	0	0	6.25	6.25	21.86

Table 2. THE NASH EQUILIBRIUM WHEN BILLING IS $\widetilde{B_n}$.

$user$	x_n^1	x_n^2	x_n^3	x_n^4	B_n
1	10	0	0	0	17.49
2	0	10	0	0	17.49
3	0	0	6.25	6.25	21.86

Next, we will compare both billing models B_n and $\widetilde{B_n}$ in terms of fairness, cost, and PAR reduction.

4.1 Fairness Comparison

For our study we choose the fairness index, denoted F, defined in [9] for comparing both billing B_n and $\widetilde{B_n}$ in terms of fairness. The value of F for B_n is $F = 0.2515$ and for $\tilde{B}_n$, we see that it reduces to $F = 0.0038$, which is 65 times less (i.e., better).

4.2 Optimality and PAR Reduction Comparison

Unlike the fairness in $\widetilde{B_n}$, the PAR reduction is not taken into consideration, also optimality in terms of cost is not guaranteed. The cost when billing is B_n is \$56.84 and becomes \$56.96 for $\widetilde{B_n}$, also PAR is 1.23 for B_n and becomes 1.53 in $\widetilde{B_n}$. All these results confirm that the index presented in Section 4.1 allows to evaluate a billing model in terms of fairness but not in terms of optimality and PAR reduction. In the next Section, first we propose a new index to evaluate billing mechanism in terms of optimality and fairness. Then our flexible billing mechanism will be presented in Section 5.2.

5 EVALUATION INDEX AND FLEXIBLE BILLING MECHANISM FOR OPTIMAL AND FAIR AUTONOMOUS DEMAND RESPONSE

To solve the problem for evaluating a billing mechanism in term of fairness, PAR reduction and optimality in Section 4, first we propose our new index to evaluate each billing scheme and use this result to evaluate billings presented in Section 4. Secondly, our flexible billing mechanism will be disused in Section 5.2 .

5.1 The new Evaluation Index

For comparing a billing model in terms of flexibility, fairness, and optimality, we introduce our evaluation index and is defined as follows:

$$F_{ev} = \lambda_1 F + \lambda_2 |PAR - PAR^*| + \lambda_3 \left| \sum_{n=1}^{N} B_n - C_{\mathcal{N}}^* \right|, \quad (6)$$

where λ_1, λ_2 and λ_3 are rates that are fixed by the utility company to evaluate such as billing mechanism. We require that $\sum_{i=1}^{3} \lambda_i = 1$. PAR is the value of PAR when using billing model and PAR^* is the optimal PAR given in a centralized fashion. We can easily calculate the values of our evaluation index for both billing models. In this case the value of F_{ev} for $\widetilde{B_n}$ is 0.142262 and we see that it reduces to 0.064762 for B_n which is 2.5 times less (i.e., better). These results motivate us for developing a new billing mechanism that consider the fairness and PAR reduction, also optimilaty. The new billing mechanism is proposed in the next Section.

5.2 The Flexible Billing Mechanism

To solve the problem with respect to fairness, PAR reduction and optimality in Section 3, we propose a new billing scheme that consider all these parameters. Let

$$\alpha_T = \sum_{i=1}^{N} (\beta_i - \alpha_i + 1)\,. \tag{7}$$

Our billing mechanism must consider the total daily load and load flexibility. For these reasons, we divided our model into two parts. The first part $\widehat{B_{n_1}}$ presents the daily load compared with the total load in the grid. The second part $\widehat{B_{n_2}}$ present user's flexibility compared with the sum of all intervals given by each user. The expressions of $\widehat{B_{n_1}}$ and $\widehat{B_{n_2}}$ are the following:

$$\widehat{B_{n_1}} = \frac{E_n}{E_T} \times \frac{E_T \times \sum_{h=1}^{H} C_h\,(L_h)}{E_T + \alpha_T (N-1)}\,, \tag{8}$$

and

$$\widehat{B_{n_2}} = \frac{\alpha_T - (\beta_n - \alpha_n)}{E_T} \times \frac{E_T \times \sum_{h=1}^{H} C_h\,(L_h)}{E_T + \alpha_T (N-1)}\,. \tag{9}$$

Our billing model is defined by:

$$\widehat{B_n} = \widehat{B_{n_1}} + \widehat{B_{n_2}} = \left[\frac{E_n}{E_T} + \frac{\alpha_T - (\beta_n - \alpha_n)}{E_T}\right] \frac{E_T \sum_{h=1}^{H} C_h\,(L_h)}{E_T + \alpha_T (N-1)}\,.$$

$$\widehat{B_n} = \left[\frac{E_n + \alpha_T - (\beta_n - \alpha_n)}{E_T + \alpha_T (N-1)}\right] \sum_{h=1}^{H} C_h\,(L_h) \tag{10}$$

According to (1) and billing in (1010), each user n seeks to solve the following local problem:

$$C_{\mathcal{N}}^* = \min_{\{x_n \in \mathcal{X}_n\}} K\, C_h\,\Big(\sum_{h=1}^{H} x_n^h + \sum_{m \in \mathcal{N}\setminus\{n\}} x_m^h\Big) \tag{11}$$

Were

$$K = \frac{E_n + \alpha_T - (\beta_n - \alpha_n)}{E_T + \alpha_T (N-1)}$$

.

As the term $\frac{E_n + \alpha_T - (\beta_n - \alpha_n)}{E_T + \alpha_T (N-1)}$ is a constant value, the problem in (11) becomes:

$$C_{\mathcal{N}}^* = \min_{\{x_n \in \mathcal{X}_n\}} C_h\,\Big(\sum_{h=1}^{H} x_n^h + \sum_{m \in \mathcal{N}\setminus\{n\}} x_m^h\Big) \tag{12}$$

As in the Theorem 1 in [4] , our billing $\widehat{B_n}$ has a unique NE in Game 1. NE when billing is as in (12) is shown in Table 3.

Table 3. THE NASH EQUILIBRIUM WHEN BILLING IS $\widetilde{B_n}$.

user	x_n^1	x_n^2	x_n^3	x_n^4	$\widehat{B_n}$
1	10	0	0	0	19.55
2	0	10	0	0	18.33
3	0	0	6.25	6.25	18.94

We can easily calculate the value of evaluation index in this case, and we see that it reduces to $F_{ev} = 0.039121$.

6 SIMULATION RESULTS

To simulate our flexible billing mechanism, we use the configuration given in [9].

6.1 PAR and Cost Comparison

The daily energy consumption as well as the corresponding PAR for the two-billing mechanism $\widetilde{B_n}$ and $\widehat{B_n}$ are presented in Fig. 1 and Fig. 2 respectively.

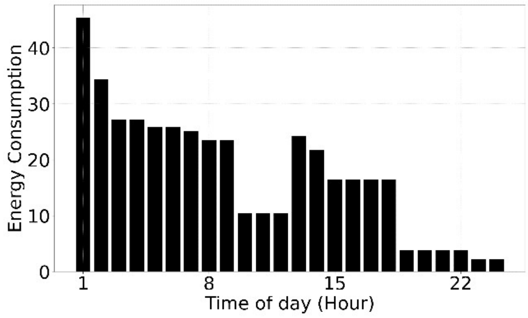

Fig. 1. Energy consumption and corresponding PAR when billing mechanism is $\widehat{B_n}$. In this case PAR is 1.2286.

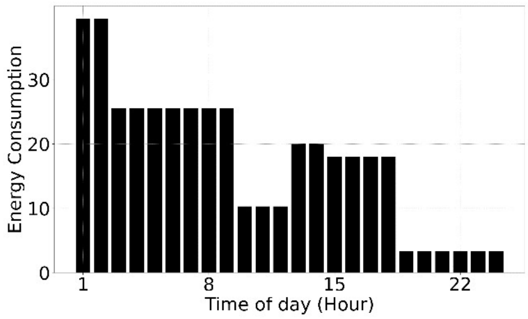

Fig. 2. Energy consumption and corresponding PAR when billing mechanism is $\widetilde{B_n}$. In this case PAR is 1.4236.

We find that the daily PAR when billing mechanism is $\widehat{B_n}$ is 1.2286 and is 1.4236 for billing mechanism $\widetilde{B_n}$ which is 14% higher. This result shows that our flexible bill achieves the PAR reduction target.

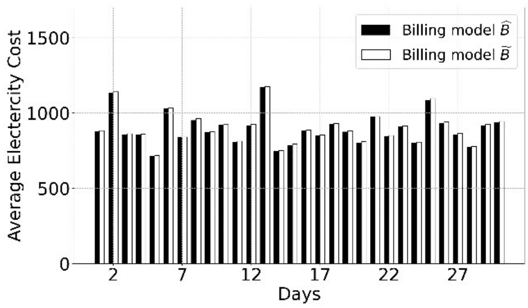

Fig. 3. Average cost.

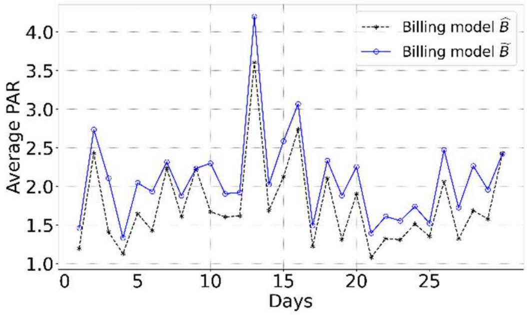

Fig. 4. Average PAR.

The average cost and PAR comparison for 30 days when billing is $\widehat{B_n}$ and $\widetilde{B_n}$ are presented in Fig. 4 and Fig. 3 respectively. The average cost when billing is $\widehat{B_n}$ is \$180.65 and is \$181.03 when billing is $\widetilde{B_n}$ that is reduced by 0.55%.

In Fig. 5 the cost versus flexibility of the users is energy of each user is fixed and the only variable that changes at each simulation step is users' flexibility. We can see that when we have more user's flexibility in the

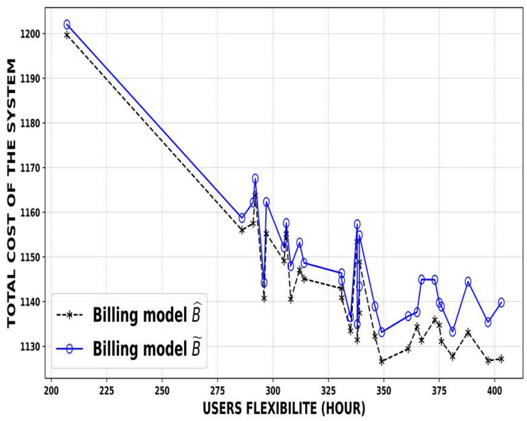

Fig. 5. Comparing Billings $\widetilde{B_n}$ and $\widehat{B_n}$ in terms of user's flexibility.

6.2 Evaluation Index Comparison

The simulation results in terms of the average of the evaluation index for both models are presented in Fig. 6.

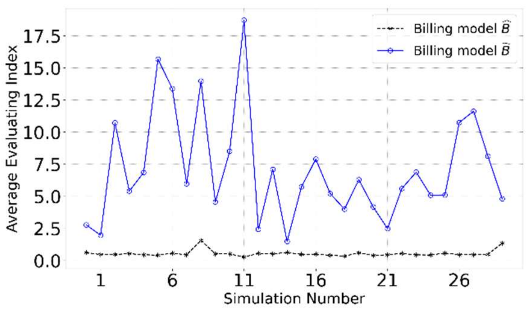

Fig. 6. Average Evaluation index.

The average value of the index for billing $\widetilde{B_n}$ is 7.10 and for our flexible billing is 0.54 which is minimized in 1214%.

Fig. 7 shows the average evaluation index value for both bills as a function of the number of users in the grid.

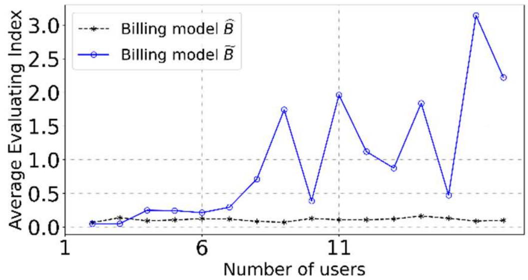

Fig. 7. Value of Evaluation index as function of user' Numbers.

As we can see, the billing model $\widetilde{B_n}$ remains more efficient for a small number of users (in this case N less than 3). In the case where the number of users is large enough, i.e., N is greater than 3, our flexible billing becomes quite efficient. This result shows that our flexible billing is more efficient in networks where the number of users registered in the grid is large enough.

7 CONCLUSIONS

In this paper, we have presented an optimal, autonomous, and distributed billing mechanism to minimize the cost, PAR and achieving fairness, also a new evaluation index to evaluate a billing model. The value of our evaluation index shows that our proposed model is performing well compared to the other models quoted in this paper. Simulation results confirm that the proposed billing mechanism can reduce the PAR, the energy cost, and optimize the bill of each user in the grid.

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