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Pareto Efficient Incentive-Based Real-Time Pricing Model for Balanced Smart Grids

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ABSTRACT In this study, a Pareto efficient incentive-based real-time pricing model was designed for balanced energy consumption scheduling (ECS) in a smart grid. In this model, the energy consumption of each subscriber is monitored and updated in real-time by an individual smart meter, and a cost-effective ECS is determined. The most recent research has not considered a balanced distribution of costs and profits to the participants. In general, there is a trade-off between service providers and subscribers. A service provider tries to maximize its profit, and a subscriber tends to minimize its cost. Therefore, the well-adjusted cost and profit distribution of a service provider and subscribers is considered by controlling the incentive degree in a Stackelberg game. The multiobjective genetic algorithm is applied to show the Pareto efficient solutions of a service provider and subscribers. Furthermore, welfare is introduced as the third objective in proposing a practical solution. It is used to select one of the multiple Pareto efficient solutions. Our model decreases subscriber costs by 9.1% and the peak-to-average ratio (PAR) by 33.2%, on average, compared with non-scheduling. The model also reduces the PAR by 11.3% and increases the provider's profit by 34.9% and total welfare by 60.0%, on average, compared with day-ahead scheduling.

INDEX TERMS Demand management, genetic algorithm, Stackelberg game, welfare.

I. INTRODUCTION

There are two major problems in current power grids: 1) inefficiency from the high peak-to-average ratio (PAR) because of uncontrolled and unpredictable energy consumption, and 2) unfairness resulting from the unbalanced distribution of the costs and benefits to participants. The former issue has been studied frequently. The PAR increases considerably during summer and winter, and residential and commercial power demands increase significantly. To address this, "peaker" power plants have been prepared in certain regions [1]. These plants are idle for most of the year and only generate electricity under urgent conditions, e.g., when the demand exceeds the upper limit of regular plants or a blackout occurs because of a technical problem in a regular plant. Consequently, such peaker plants have an intrinsically low efficiency and must charge more for electricity. To address this problem, several studies on such solutions as real-time pricing (RTP)-based consumption scheduling and contract-based consumption scheduling [2]–[5] have been conducted. On the manufacturing side, the factory manager tries to minimize production costs by avoiding peak-time consumption through load shifting [6]. A load aggregation method from generation-follows-load to load-follows-generation was proposed based on the perspective of the provider [7]. In particular, to manage sudden load changes and reduce the PAR, a combination of forecasting, shedding, and smart direct load control by the Internet of things has been proposed [8], [9]. However, recently, residential and commercial subscribers have begun to consider rescheduling energy consumption for more-effective cost and utility management [10], [11].

In such a condition, the balanced distribution of costs and benefits to subscribers and providers has not been considered in detail because of a lack of information and interest conflicts among participants, even though an imbalance frequently occurs [12]–[15]. Recently, the importance of fairness in smart grids has been emphasized. Many studies have considered the fairness of subscribers in the power grid, especially for balanced cost distribution among subscribers,

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based on their energy consumption [16]–[18]. Javed *et al.* considered the fairness of subscribers by proposing a fair dynamic pricing model using unsupervised learning [19]. They clustered the subscribers into several groups and generated an appropriate hourly price for each group. However, they did not consider the perspective of each subscriber. Jacquot *et al.* analyzed dynamic pricing models for demand management in terms of effectiveness and fairness [20]. Ren *et al.* developed and compared collaboration optimization and cooperative game models in distributed energy networks for effectiveness and fairness, respectively [21]. However, these studies only considered the fairness of consumers/prosumers. In other words, they did not address the profit distribution between a service provider and consumer sides. Jing *et al.* proposed a Nash game-theoretic model for a non-cooperative game among prosumers for a fairer profit distribution [22]. However, their model is difficult to apply if the number of prosumers increases owing to the complexity of the model. Seok and Kim invented a modified RTP model by measuring the sacrifice level of each subscriber and achieved a fairer network [5]. Moreover, an approach in terms of fair delay of energy usage instead of fair bill comparison has been proposed [23].

However, to the best of the authors' knowledge, the effect of energy consumption scheduling on two conflicting interests, service provider profit maximization and subscriber cost minimization, has not been analyzed and compared. Previous consumption scheduling models have not considered the balancing of the two sides because it is difficult to define and estimate. Advanced electricity pricing and consumption scheduling are necessary to achieve a sustainable power grid by collaborating with a service provider and subscribers.

Therefore, an intelligent, balanced pricing and consumption scheduling model for a smart grid that uses Pareto efficiency is proposed, the Pareto efficient incentive-based RTP model. In Pareto efficiency, either a service provider or subscribers cannot be better off without making the opponent worse off. The proposed model is based on a Stackelberg game between a service provider and subscribers. The service provider acts as a leader, determining the unit electricity price at first. Each subscriber acts as a follower, determining an appropriate consumption schedule accordingly. The game is a traditional problem in power grids [3], [24], [25]. The price is updated in real time, i.e., the RTP-based model is applied. The model uses an incentive factor to control the cost/benefit distribution of the service provider and subscribers. An appropriate value of the incentive degree is determined that controls how much the sacrifice of subscribers is considered in their bills. In other words, how much the consumption of a subscriber is relocated is reflected in calculating the bill. Depending on the value of the incentive degree, the electricity unit cost charged to each subscriber in each time slot can be different, and the portion of the profit of the service provider from each subscriber can also vary.

The Pareto efficient front between a service provider and subscribers is obtained using a genetic algorithm (GA) that searches for an appropriate value of the incentive degree. The concept of welfare in economics was utilized to suggest a practical solution among Pareto efficient solutions, i.e., the solution where the total benefit minus the total cost is the largest [26]. Recently, several studies have focused on this welfare aspect in smart-grid management. Paramathma *et al.* developed artificial neural network and GA models to find the optimal bidding price and penalty cost for each consumer by determining the load schedule with curtailment [27]. However, they did not consider the bilateral relationship between service providers and consumers. Oh and Son proposed a peer-to-peer (P2P) energy transaction model to maximize social welfare by aggregating all producers and consumers while considering the fairness of profit distribution [28]. They treated fairness as a constraint rather than an independent objective. Bedoya *et al.* proposed a distributed algorithm to optimize social welfare, e.g., minimizing the operation cost while maximizing supplier surplus. However, the objectives and constraints in their model had to be represented as linear [29]. In the present study, the welfare objective is considered as well as the profit and fairness of profit distribution among participants. In addition, nonlinear functions are applicable to the proposed model.

In this study, it was assumed that a smart grid consists of millions of pieces and parts: meters, controllers, computers, power lines, and communication equipment [4]. Each participant in a network, such as a generator, service provider (transmission, switchyard), and subscribers, has individual control and a communication tool called the "energy management controller" (EMC). Moreover, each participant acts independently and is self-interested. A smart grid makes it possible to expect the consumption of subscribers and the electricity unit price through real-time communication among participants. Based on such shared information, each subscriber can determine a more cost-effective energy consumption schedule, and the service provider can determine the appropriate price to maximize the profit [30]. In this study, the part of a smart grid consisting of the service provider and subscribers (red dashed box in Fig. 1) is considered.

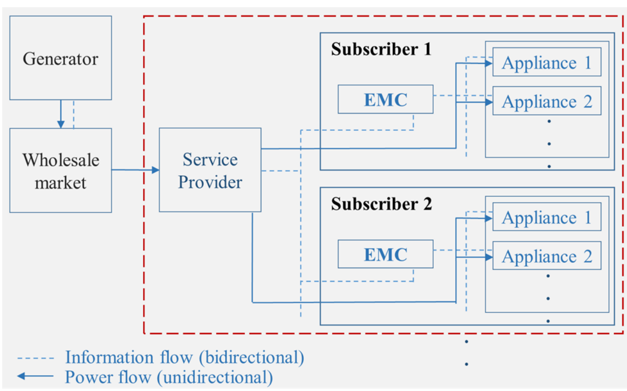

FIGURE 1. Framework of smart grid.

The remainder of this article is organized as follows. Previous studies are reviewed in Section II, and the Pareto efficient incentive-based RTP model is described in Section III. The empirical demonstration of the performance of the proposed model is described in Section IV, and conclusions and future work are discussed in Section V.

II. BACKROUND RESEARCH

A. ENERGY SCHEDULING CONSUMPTION MODELS

Various pricing and consumption scheduling models have been developed to mitigate price and consumption volatility with a high PAR. In particular, as smart grids become available globally, it is essential to bring the electricity network into the information age using digital technology. Many elaborate models have been suggested [26], [31]–[33]. Day-ahead optimization has been proposed as a centralized model [32], [33]. The electricity unit price in each time slot is determined by the supply side in the day-ahead market clearing process [32]. Based on the price, a centralized decision-making unit determines the optimal consumption schedule of subscribers and the planned supply. Moreover, subscribers strictly follow a predetermined schedule, regardless of changes in conditions. However, this condition is unreasonable in reality. In addition, such a centralized model becomes inefficient as the number of subscribers increases, requiring additional computational time. Moreover, there is a risk of private information leakage. Hence, a distributed decision-making model has been suggested as an alternative method.

Distributed energy consumption models can consider the multilaterally satisfied decisions of subscribers and service providers. To manage the trade-off among participants, a game-theoretic approach is applied. A Nash equilibrium in a Cournot game among subscribers and a Stackelberg game between a service provider and subscribers has been used to suggest an optimal price and consumption schedule [24], [25]. Mohsenian-Rad *et al.* proposed a distributed algorithm derived from a game-theoretic relationship between subscribers and a service provider; however, it only considers the objective of subscribers, i.e., subscriber cost minimization [3]. Thereafter, Chen *et al.* developed an innovative RTP model supported by a Stackelberg game between subscribers and a service provider [24]. In the model, backward induction is used to obtain an equilibrium price and corresponding schedule consumption. In the present study, a Stackelberg game was modeled and applied to find the balanced price and consumption schedule of subscribers by considering the needs of a service provider and subscribers.

Furthermore, several drawbacks of the previous studies were addressed. Most previous research used time-slot-based scheduling, regardless of the actual continuous usage of specific appliances [8], [25], [34], [35]. Moreover, a penalty cost caused by a delay in consumption reallocation was not considered. The total consumption usage was considered instead, but the continuity of energy usage per appliance was neglected [30]. Hence, the model proposed in the present study utilizes appliance-based scheduling to be more realistic and considers a penalty cost for the inconvenience of relocated consumption. Furthermore, the objective function of a service provider includes a mismatch cost owing to the gap between the actual consumption and planned supply.

B. PARETO EFFICIENT INCENTIVE-BASED RTP MODEL

In most RTP-based models [3], [24], subscribers relocate their consumption according to the price provided by a service provider, which is predicted based on the total load per time slot. However, this method is ineffective for price-insensitive subscribers, and there is a lack of fairness in the distribution of costs and benefits [36]. Tsaousoglou *et al.* proposed a personalized RTP model for the fairness and cost reduction of subscribers [37]. However, to the best of the authors' knowledge, an individually different electricity unit pricing depending on the price sensitivity and degree of sacrifice of each subscriber has not been investigated.

In previous studies, the electricity unit price in the same period was assumed to be the same for all subscribers. In the consumption scheduling models, each subscriber relocates usage according to the given price and utility function (price sensitivity). Hence, some subscribers are more likely to relocate their intended consumption to another period, such as an off-peak period. In contrast, subscribers who are relatively price-insensitive tend to maintain their preferred consumption schedules. In such a condition, a price-insensitive subscriber who does not sacrifice to change use schedules can obtain a free advantage from the rescheduling of price-sensitive subscribers, especially during peak times. Borenstein *et al.* discussed the importance of the fair redistribution of electricity prices for such a low-income census (i.e., price-sensitive subscribers) [2]. Aurangzeb *et al.* designed a fair pricing scheme, especially for low-energy consumers, based on load consumption forecasting by machine learning [38]. However, both studies achieve fairness only for a specific group of consumers. To address this weakness, an individually different electricity unit pricing model was designed that depends on the total load per time slot and sacrifice degree of each subscriber [5]. As a result, the proposed incentive mechanism prompts more subscribers to relocate their power use and better distribute subscriber costs.

In the present study, the need of the service provider to maximize profits is also considered. The previous scheduling models did not consider the balanced cost and benefit distribution to subscribers and service providers. Subscriber cost minimization and utility maximization have been the focus of most previous studies [16], [17]. Baharlouei and Hashemi studied the trade-off between the efficiency and fairness of subscribers in a smart grid [16]. They designed a billing mechanism to enhance the fairness of subscriber bills by considering subscriber flexibility in pricing. Zhang *et al.* also considered fairness enhancement of smart homes in smart buildings with distributed energy resources and storage [17]. They developed mixed-integer linear programming to determine the consumption schedule of each home and the production plan, considering the fair distribution of cost among homes and minimizing total cost. However, estimating the extent of the balance is difficult. Moreover, there is no factor for adjusting the degree of balance.

Many methodologies have been applied to deal with multiple objectives among participants in the smart grid, such as the evolutionary algorithm [39], the bat algorithm [40], genetic algorithms [41], particle swarm optimization [42], and the whale optimization algorithm [43]. Soriano *et al.* designed an autonomous model integrating the multiobjective bat algorithm, Pareto front, and fuzzy decision-making models [40]. They considered two objectives: decreasing expenses in electrical energy purchasing and increasing the electrical energy sale profits of each participant. However, they assumed that the P2P trading problem was strictly convex. In addition, the scale of the objective functions was normalized. Aghajani and Ghadimi proposed a multiobjective particle swarm optimization model to address demand management in microgrids, harmonizing the minimization of operating costs and pollution emissions [42]. They showed the distribution of the Pareto criterion of the two objectives. Their approach is similar to that of the present study. Li *et al.* developed an adaptive reference point based on a large-scale multiobjective whale optimization algorithm that divides and conquers a cluster of decision variables [43]. They considered the objectives of various participants but did not include fairness and welfare. To the best of the authors' knowledge, studies that consider the profit, fairness of profit distribution, and welfare of a network in demand management using a GA have not been conducted. In addition, the GA can effectively handle nonlinear functions.

Hence, in this study, the balance between subscriber costs and service provider profit is achieved by applying Pareto efficiency with the GA. By controlling the value of the incentive factor, called the "incentive degree," one can not only carefully reduce subscriber costs but also balance the cost and profit distribution between subscribers and a service provider. More details regarding this model are provided in Section III.

III. METHODOLOGY

A residential power system comprising a service provider and subscribers is considered (Fig. 1). A service provider purchases electricity from the wholesale market and sells it to subscribers. The energy consumption schedule of each subscriber is determined by its own controller (EMC) according to the informed price by the service provider and the decision mechanism. After the final schedule of each subscriber is determined, the service provider sends the corresponding electricity. In this study, transferable energy consumption was considered.

The RTP model proposed by Chen *et al.* [24] was modified. The price function was changed to be continuous, and the method for charging the electricity unit cost was revised. This was based on the incentive degree and sacrifice degree of each subscriber. Depending on the consumption rearrangement degree of each subscriber, i.e., the sacrifice degree, the electricity unit cost is different, even in the same time slot.

There are n_s subscribers ($n = 1, 2, \ldots, n_s$). Each subscriber has n_a appliances ($a = 1, 2, \ldots, n_a$). The energy consumption schedule of the subscriber during T time slots is considered ($t = 1, 2, \ldots, n_t$).

NOTATION

n	subscriber $n (n = 1, 2, \ldots, n_s)$
a	schedulable appliance $a (a = 1, 2, \ldots, n_a)$
t	time slot $t (t = 1, 2, \ldots, n_t)$
N	set of subscribers ($n \in N$)
A	set of schedulable appliances ($a \in A$)
A_n	set of schedulable appliances of subscriber n
T	set of time slots ($t \in T$)
L	number of repetitions
$l_{n,a}$	operation duration of appliance $a \in A_n$
$c_{n,a}$	power usage (kW) of appliance $a \in A_n$
$\phi_{n,a}$	penalty cost of appliance $a \in A_n$ per slot due to the delay
$o_{n,a}$	initial requested starting time of appliance $a \in A_n$
$s_{n,a}$	starting time of appliance $a \in A_n$ (a subscriber's decision variable)
$d_{n,a}$	maximum allowable delay of appliance $a \in A_n$
ω	electricity unit price coefficient (service provider's decision variable, $\omega \geq 1$)
γ	incentive degree (decision variable of the Pareto efficient RTP model, $0 \leq \gamma \leq 1$)
q_t	planned supply for time slot t
z_t	actual consumption for time slot t
α	wholesale price coefficient
θ_t	wholesale price per unit electricity in time slot

$$\theta_t = \alpha \cdot q_t \tag{1}$$

ϵ_t additional price due to the gap between planned supply and actual consumption in time slot t.

$$\epsilon_t = \frac{g(q_t, z_t, \omega)}{\sum_{t=t_0}^{T} g(q_t, z_t, \omega)} \cdot M_{t_0} \tag{2}$$

$$g(q_t, z_t, \omega) = \begin{cases} \dfrac{1}{(q_t - z_t + 1)^{\omega}} & q_t > z_t \\ (z_t - q_t + 1)^{\omega} & q_t < z_t \\ 0 & q_t = z_t \end{cases} \tag{3}$$

* $\sum_{t=t_0}^{T} \epsilon_t = M_{t_0} = \sum_{t=t_0}^{T} \epsilon_0$; ϵ_0 is the comparable constant price gap in some (alternate) fixed rate pricing scheme.[1]

$p_{n,a,t}$ power consumption of appliance $a \in A_n$ in time slot t.

pp_n total delay cost of subscriber n

$$pp_n = \sum_{a \in A_n} \left(s_{n,a} - o_{n,a}\right) \cdot \phi_{n,a} \tag{4}$$

ap average delay cost of subscribers.

β mismatch cost coefficient.

δ_n sacrifice degree of subscriber n

$$\delta_n = (pp_n - ap)/ap \tag{5}$$

$\epsilon_{n,t}$ individualized ϵ_t of subscriber n in time slot t.

$$\epsilon_{n,t} = (1 - \gamma \cdot \delta_n) \cdot \epsilon_t \tag{6}$$

$\pi_{n,t}$ retail price of subscriber n in time slot t

$$\pi_{n,t} = \theta_t + \epsilon_{n,t} \tag{7}$$

TC total costs of subscribers when incentive mechanism is applied.

TC^0 total costs of subscribers without incentive mechanism ($\gamma = 0$).

TP profit of service provider when incentive mechanism is applied.

TP^0 profit of service provider without incentive mechanism ($\gamma = 0$).

Fit_s objective function (fitness function) of GA in terms of subscriber side

$$Fit\_s = (TC - TC^0) \tag{8}$$

Fit_p objective function (fitness function) of GA in terms of service provider side[2]

$$Fit\_p = -(TP - TP^0) \tag{9}$$

TW total welfare (benefit of participant minus total cost of participant) when incentive mechanism is applied[3]

$$\begin{aligned} TW = &\left\{ \sum_{alln,a} \sum_{t=s_{n,a}}^{s_{n,a}+l_{n,a}} \pi_{n,t} \cdot p_{n,a,t} \right. \\ &\left. - \sum_{t=1}^{T} \beta\,(z_t - q_t)^2 \right\} \sum_{alln,a} \sum_{t=s_{n,a}}^{s_{n,a}+l_{n,a}} \left\{ \left(s_{n,a} \right.\right. \\ &\left.\left. - o_{n,a}\right) \cdot \phi_{n,a} + \pi_{n,t} \cdot p_{n,a,t} \right\} \\ = &- \left\{ \sum_{alln,a} \sum_{t=s_{n,a}}^{s_{n,a}+l_{n,a}} \left(s_{n,a} - o_{n,a}\right) \cdot \phi_{n,a} \right. \\ &\left. + \sum_{t=1}^{T} \beta\,(z_t - q_t)^2 \right\} \end{aligned} \tag{10}$$

TW^0 total welfare without incentive mechanism ($\gamma = 0$).

Fit_w objective function (fitness function) of GA, in terms of the total welfare aspect

$$Fit\_w = -(TW - TW^0) \tag{11}$$

Here, Eqs. (1), (2), (3), and (7) from the previous RTP-based model proposed by Chen *et al.* [24] are referred to. The retail price, $\pi_{i,t}$, by a service provider is the sum of the wholesale price, θ_t, and the price gap, ϵ_t, as in Eq. (7). The wholesale price influences the EMC scheduling so that the peak load is reduced while the price gap decreases. The wholesale price, θ_t, is defined in Eq. (1). The price gap, ϵ_t, is designed to influence the difference between the actual demand, z_t, and the planned supply, q_t. Here, ϵ_t is designed to be proportional to $g\,(q_t, z_t, \omega)$, and it decreases with q_t minus z_t, i.e., the larger the value of q_t minus z_t, the lower the price gap, ϵ_t, so that the EMC is more likely to schedule the appliance to operate during this period, and vice versa [24]. If an appliance requests to start at time slot t_0, ϵ_t is calculated using Eq. (2). Here, $g\,(q_t, z_t, \omega)$ is set as in Eq. (3) and ϵ_t as in Eq. (2). The price function was partially revised to make it continuous, and the method of computing the electricity unit cost per individual using Eqs. (5)–(7) was modified. The electricity unit cost varies among customers depending on the degree of shift in the consumption of each subscriber, which is called the "degree of sacrifice." This value can be calculated by comparing the delay cost of each subscriber with the average delay cost of the subscribers using Eq. (5). Based on the degree of sacrifice, the individualized ϵ_t is calculated as in Eq. (6). Finally, the retail price of each subscriber is calculated and affected by the degree of sacrifice and the incentive degree, as in Eq. (7).

A. SERVICE PROVIDER ASPECT

A service provider attempts to maximize its profits — see Eq. (12). After a subscriber submits a consumption schedule, the service provider solves Eq. (12) and updates ω^*. The service provider then notifies subscribers of the updated price information. The first term, $\epsilon_{n,t} \cdot p_{n,a,t}$, is the net profit from subscribers, and the second term, $\beta\,(z_t - q_t)^2$, is the mismatch cost from the gap between the planned supply and actual consumption. Moreover, ω^* is obtained by backward induction [44]. The set of feasible discrete ω values is used, $\Omega = \{\omega_1, \omega_2, \ldots, \omega_W\}$, where $W = |\Omega|$.

$$\max_{\omega\in\Omega} \sum_{t=1}^{T} \sum_{n\in N} \sum_{a\in A_n} \epsilon_{n,t} \cdot p_{n,a,t} - \beta\,(z_t - q_t)^2 \tag{12}$$

B. SUBSCRIBER ASPECT

After a service provider informs subscribers of the current price information, each subscriber finds $\boldsymbol{s_{n,a}}^*$ to minimize subscriber cost and notifies the service provider of this cost.

$$\begin{aligned} &\min_{s_{n,a}} \left(s_{n,a} - o_{n,a}\right) \cdot \phi_{n,a} + \sum_{t=s_{n,a}}^{s_{n,a}+l_{n,a}} \pi_{n,t} \cdot p_{n,a,t} \\ &\text{s.t.}\, o_{n,a} \le s_{n,a} \le o_{n,a} + d_{n,a},\, s_{n,a} + l_{n,a} \le T \end{aligned} \tag{13}$$

C. PARETO EFFICIENT INCENTIVE-BASED RTP

Algorithm 1 describes the performance of the proposed model. From the iterative decision process between a service provider and each subscriber, the equilibrium points of ω^* (by a service provider) and $s_{n,a}{}^*$ (by each subscriber) are obtained. They then update $\pi_{n,t}$ and z_t using two-way communication. Here, γ^* is independently obtained using a GA.[4]

After an initial setting (Step 0), a service provider updates the price information (Step 1, SP). Thereafter, for each time slot, Subscriber i finds and updates $s_{i,k}{}^*$ by considering the current price information and consumption schedule, $\pi_{i,t}$ and z_t, respectively, updates z_t, and then notifies a service provider of all of this (Step 1, SB). A service provider then updates ω^* and the price information again and notifies Subscriber i of this (Step 1, SP). Based on the updated information, Subscriber i finalizes $s_{i,k}{}^*$, updates z_t, and sends the information back to the service provider (Step 2, SB). Finally, a service provider updates ω^* and the price information (Step 1, SP). This procedure is repeated within each individual of each generation in the GA. Three fitness measures are used: Fit_s, Fit_p, and Fit_w, i.e., three objectives. The Pareto front is shown in Fig. 3.

In this model, γ^* is continuously updated/recorded until the exit condition of the GA is satisfied. After the Pareto efficient γ^* is found by the GA, i.e., the Pareto front is plotted, as in Figs. 2–3,[5] some value of γ^* is applied to the L repetitions to obtain the average performance of several measures, e.g., TC, TP, TW, and PAR (Figs. 4–7). Detailed results are discussed in the following section.

IV. EXPERIMENTAL RESULTS

Appliances have an on-peak period from 5:00 p.m. to 8:00 p.m., i.e., they consume more electricity then. Settings reported previously [24] are referred to, and the value of α is updated based on an earlier study [45]. The 80 subscribers are homogeneous; thus, depending on the appliance type, $c_{n,a}$, $l_{n,a}$, $\varphi_{n,a}$, and $d_{n,a}$ are given as described in Table 1. Here, $l_{n,a}$ follows an exponential distribution with a mean of $\overline{l_{n,a}}$.

TABLE 1. Parameter setting I.

Appliance type	$c_{n,a}$ (kW)	$\phi_{n,a}$ (\$/h)	$\overline{l_{n,a}}$ (h)	$d_{n,a}$ (h)
1	1.8	6	0.10	3.0
2	3.4	4	0.25	1.0
3	0.4	2	0.40	0.5

TABLE 2. Parameter setting II.

Parameter	Value
α	5.6e–04
β/α	0.5
ϵ_0/α	20

Each time slot is 10 min, T is 144 (24 h), and L is 300. Other price- and cost-related parameters are listed in Table 2.

[4]Here, γ^* is the best solution obtained by the GA.

[5]A three-dimensional Pareto efficient front is described in Fig. 3, and Fig. 2(a) represents the same Pareto front but as a two-dimensional one: a service provider profit and subscriber costs. Fig. 2(b) represents the score diversity for each objective.

Algorithm 1 Pareto Efficient Incentive-Based RTP Model

Genetic algorithm for multiple objectives (gamultiobj) to find $\boldsymbol{\gamma}^*$

Initial Setting: Subscribers set the initial consumption schedule; service provider collects the information.

Until the exit condition[6] is satisfied.

Service provider's side (SP)	Subscribers' side (SB)
Step 1 (SP): Update ω^* by Eq. (12) and price information, and send the updated price information to subscribers.	
	For $t = 1 : n_t$ **For** $i = 1 : n_s$ **For** $j = 1 : n_a$ If any appliance, of which $s_{i,k} = t$, exists; **Step 1 (SB):** Find $s_{i,k}{}^*$ by Eq. (13); Send the corresponding information to service provider. **Step 2 (SB):** Based on the updated price information, find $s_{i,k}{}^*$ and update z_t, accordingly. Send the information to service provider. **End** **End** **End** **End**

End

*Sequence of procedure: Step 1 (SP) - Step 1 (SB) - Step 1 (SP) - Step 2 (SB) - Step 1 (SP) - Step 1 (SB) …

To validate the performance, three scheduling models are compared: 1) nonscheduling (M1), 2) day-ahead scheduling (M2), and 3) the proposed model (M3). The simulation experiments were coded using MATLAB.

Fig. 2(a) represents the Pareto front as two dimensional, i.e., between service provider profit and subscriber costs. Any star point in the Pareto front can be an efficient solution. This represents the set of consumption states wherein it is impossible to make subscribers or service providers better off without making the opponent worse off. Choosing one of the

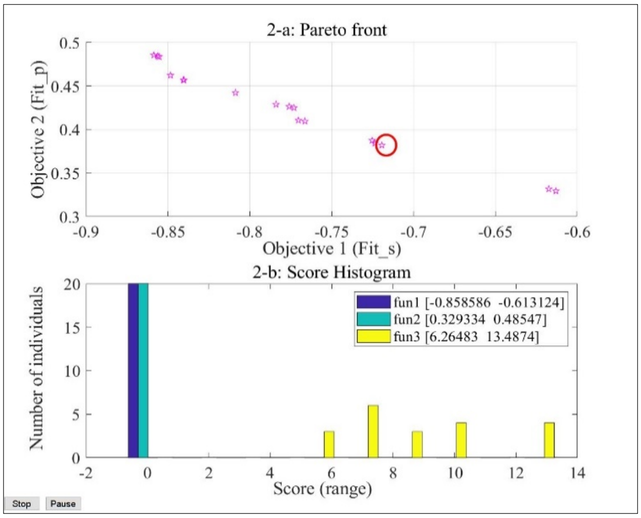

FIGURE 2. Pareto efficient surface by GA (fun1: Fit_s, fun2: Fit_p, fun3: Fit_w).

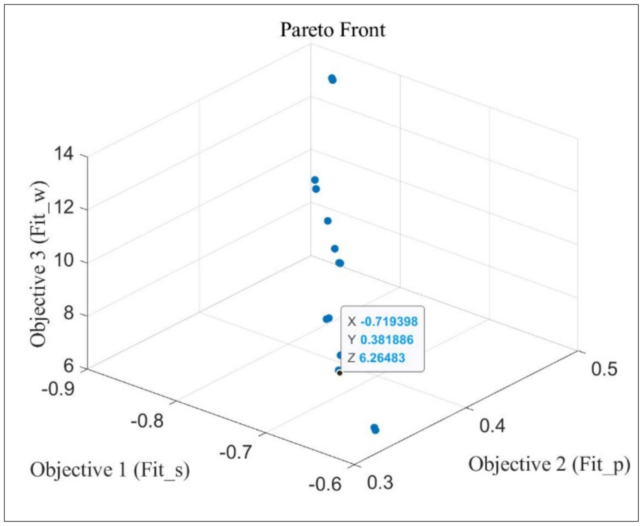

FIGURE 3. Pareto efficient three-dimensional surface by GA.

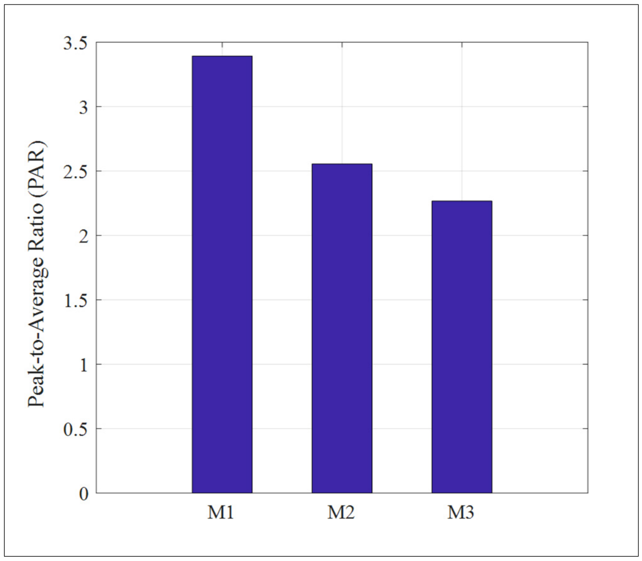

FIGURE 4. PAR of three scheduling models.

states is associated with distributing the costs and benefits to both parties. As the star moves from the left upper corner to the bottom right corner, the incentive degree becomes smaller ($0 \leq \gamma \leq 1$).

For guidance, when $\gamma = 0$, subscriber costs are decreased by an average of 8.0% compared with nonscheduling. The PAR and service provider profit are decreased by an average of 35.7% and 20.3%, respectively, compared with those of nonscheduling. However, when $\gamma = 1$, subscriber costs are decreased by an average of 26.9%, in contrast to nonscheduling, and the PAR and service provider profit are decreased by, on average, 33.9% and 72.8%, respectively, compared with those of nonscheduling. This is intuitively understandable. As the incentive degree increases, subscribers take more advantage of it by active consumption relocation, i.e., subscribers can reduce the cost while the service provider profit decreases.

Hence, the third fitness value, *Fit_w*. as in Eq. (11), was used to provide a practical solution. The point with the highest *TW* (the smallest *Fit_w*) is shown in Fig. 2(a) and Fig. 3. Fig. 2(b) represents the individual scores of the three fitness measures *Fit_s*, *Fit_p*, and *Fit_w*. The ranges of *Fit_s*, *Fit_p*, and *Fit_w* are approximately between -0.86 and -0.61, between 0.33 and 0.49, and between 6.26 and 13.49, respectively. Table 3 presents a summary of the GA results.

TABLE 3. Summary of GA result.

Optimization terminated: maximum number of generations exceeded.
Number of generations: 50
Number of function evaluations: 2551
Number of points on the Pareto front: 20
Average distance measurement of the solutions on the Pareto front: 0.0083
Spread measurement of the Pareto front: 0.1172

To recognize the position of the marked point in Fig. 2(a) more clearly, a three-dimensional Pareto efficient front is shown in Fig. 3, and the corresponding point is marked with data. When the incentive degree at the point is applied, subscriber costs decrease on average by 9.1%, the PAR decreases by 33.2%, and the service provider profit decreases by 22.4%, on average, compared with nonscheduling (Figs. 4–6). Even though the *TW* of the proposed model is lower than that of nonscheduling (*TW* of M1: -8.7, *TW* of M3: -16.4), M3 achieves a significant reduction in the mismatch cost (Fig. 7). This result is reasonable because the satisfaction of subscribers regarding utility is not considered when calculating *TW*. In the same context, M1 has a serious inefficiency problem because of its high PAR. However, in the case of M2, subscriber costs are lower than those of the other models. However, the service provider profit is also the lowest, and there is a high mismatch cost problem because of the low efficiency.

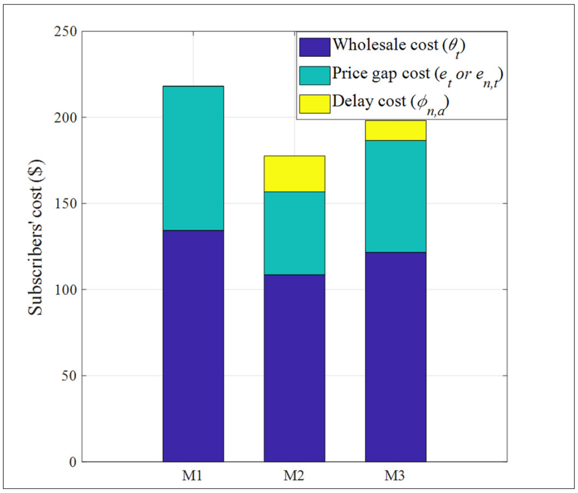

FIGURE 5. Subscriber costs of three scheduling models.

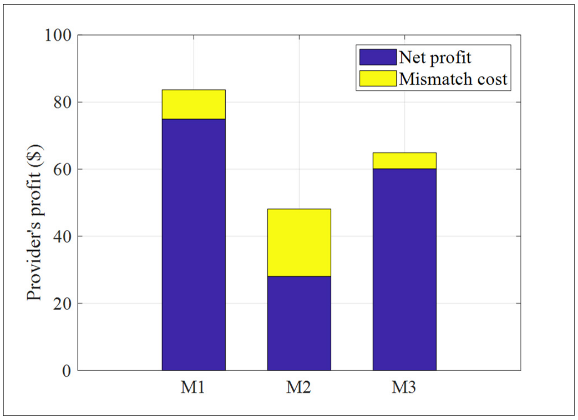

FIGURE 6. Service provider profit of three scheduling models.

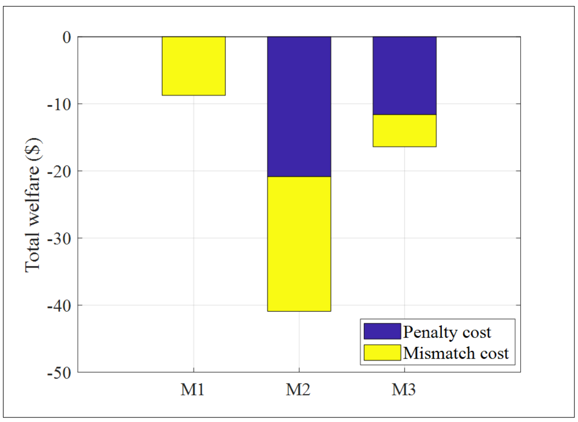

FIGURE 7. Total welfare of three scheduling models.

The results indicate that there is no universal solution to satisfy all objectives: low subscriber costs and a high service provider profit, as well as a low PAR. Furthermore, because there is a trade-off among the objectives of participants, the solution negotiated by an appropriate model must be addressed in reality. Hence, in the present study, considering the aspect of the total welfare in the model is proposed, as described above.

V. CONCLUSION

In this study, the unbalanced distribution of costs and benefits to the participants in a smart grid was addressed. A Pareto efficient incentive-based RTP model was developed that can control the degree of cost and benefit distribution to subscribers and a service provider. To balance the conflicting interests of both sides, the concept of welfare was introduced as a third objective and used to find the most appropriate Pareto efficient solution. As a result, our model lowers subscriber costs by 9.1% and the PAR by 33.2%, on average, compared with non-scheduling. The model also decreases the PAR by 11.3% and increases the provider's profit by 34.9% and total welfare by 60.0%, on average, compared with day-ahead scheduling.

However, the Pareto efficient front depends highly on the characteristics of the subscribers. Hence, in the future, the model should be extended. Heterogeneous subscribers should be considered. In particular, the effects of different incomes and electricity use patterns of each subscriber on the general performance of a Pareto efficient incentive-based RTP model should be analyzed. Various negotiated solutions need to be investigated by applying other objectives, such as various fairness measures.

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