Optimal Day-ahead Dynamic Pricing of Grid-connected Residential Renewable Energy Resources Under Different Metering Mechanisms

Kimia Parandeh, Abed Bagheri, and Shahram Jadid

***Abstract*—Nowadays, grid-connected renewable energy resources have widespread applications in the electricity market. However, providing household consumers with photovoltaic (PV) systems requires bilateral interfaces to exchange energy and data. In addition, residential consumers' contribution requires guaranteed privacy and secured data exchange. Day-ahead dynamic pricing is one of the incentive-based demand response methods that has substantial effects on the integration of renewable energy resources with smart grids and social welfare. Different metering mechanisms of renewable energy resources such as feed-in tariffs, net metering, and net purchase and sale are important issues in power grid operation planning. In this paper, optimal condition decomposition method is used for day-ahead dynamic pricing of grid-connected residential renewable energy resources under different metering mechanisms: feed-in-tariffs, net metering, and net purchase and sale in conjunction with carbon emission taxes. According to the stochastic nature of consumers' load and PV system products, uncertainties are considered in a two-stage decision-making process. The results demonstrate that the net metering with the satisfaction average of 68% for consumers and 32% for the investigated electric company leads to 28% total load reduction. For the case of net purchase and sale mechanism, a satisfaction average of 15% for consumers and 85% for the electric company results in 11% total load reduction. In feed-in-tariff mechanism, in spite of increased social welfare, load reduction does not take place.**

***Index Terms*—Dynamic pricing, renewable energy resources, feed-in-tariffs, net metering, net purchase and sale, stochastic decision-making.**

NOMENCLATURE

A. Indices and Sets

h	Index of time
I	Index of residential consumers
k	Index of iterations
s	Index of scenarios

B. Parameters

α	Utility function parameter
δ	Energy storage cost
θ	Charging/discharging rate of battery storage up to its maximum capacity
γ	Maintenance and installation cost of energy storage
σ	Average cost of renewable energy
π_{demand}	Probability of each subscriber's demand scenario
π_{PV}	Probability of PV generation scenario
π_s	Probability of each scenario
$\bar{\lambda}_h$	Electric company's electricity selling price in the first stage of decision-making
$\bar{\mu}_h$	PV generation price sold to electric company in the first stage of decision-making
$\overline{\lambda s}_{h,s}$	Electric company's electricity selling price in the second stage of decision-making
$\overline{\mu s}_{h,s}$	PV generation price sold to electric company in the second stage of decision-making
a, b, c	Electric company's cost function parameters
B_0	Initial storage capacity
$B_i^{\max}$	The maximum storage capacity
$\overline{Go}_{i,h}$	PV power sold to power grid under net metering and net purchase and sale in electric company's subproblem
$\overline{go}_{i,h,s}$	PV power sold to power grid under net metering and net purchase and sale in electric company's subproblem in each scenario
$g_{i,h,s}$	Residential consumers' PV generation in each scenario
$\bar{g}_{i,h,s}$	Households' PV generation in electric company's subproblem in each scenario
$G_i^{\max}$	The maximum capacity of PV systems
$\bar{G}_{i,h}$	Households' deterministic PV generation value in electric company's subproblem
$\bar{L}_h$	Electric company's total deterministic generated electricity in household customer's subproblem
$\bar{l}_{h,s}$	Electric company's total stochastic generated

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	electricity in household customer's subproblem
$L_h^{\max}$	The maximum value of electric company's electricity production
$L_h^{\min}$	The minimum value of electric company's electricity production
m, n	Carbon emission parameters
$\bar{Q}_h$	Electric company's total deterministic purchased renewable energy in household customer's subproblem
$\bar{q}_{h,s}$	Electric company's total stochastic purchased renewable energy in household customer's subproblem
$R_{i,h}^{+\max}$	The maximum storage charging capacity
$R_{i,h}^{-\max}$	The maximum storage discharging capacity
$\bar{R}_{i,h}^{+}$, $\bar{R}_{i,h}^{-}$	Deterministic storage charging and discharging rates in electric company's subproblem
$\bar{r}_{i,h,s}^{+}$	Storage charging/discharging in electric company rate in each scenario
$T_{\max}$	The maximum value of electric company's purchased renewable electricity
$w_{i,h}$	Subscriber's preference
$X_{i,h}^{\min}$	The minimum value of customer's electricity consumption
$X_{i,h}^{\max}$	The maximum value of customer's electricity consumption
$x_{i,h,s}$	Residential consumers' demand in each scenario
$\bar{X}_{i,h}$	Households' deterministic demand value in electric company's subproblem
$\bar{x}_{i,h,s}$	Households' demand value in electric company's subproblem in each scenario
$\bar{x}_{i,h,s}^{shed}$	Load shedding in electric company's subproblem in each scenario

C. Variables

$C(L_h)$	Electric company's deterministic cost function
$CS(l_{h,s})$	Electric company's stochastic cost function
$DR(Y_{i,h})$	Cost of selling electricity to grid
$DS(R_{i,h}^{\pm})$	Deterministic cost of electricity storage
$DR_s(y_{i,h,s})$	Stochastic cost of selling electricity to power grid
$DS_r(r_{i,h,s}^{\pm})$	Stochastic cost of electricity storage
$G_{i,h}$	Households' deterministic PV generation
$Gi_{i,h}$	Consumed PV power under net metering and net purchase and sale
$Go_{i,h}$	PV power sold to power grid under net metering and net purchase and sale
$go_{i,h,s}$	PV power sold to power grid under net metering and net purchase and sale in each scenario
$H(Q_h)$	Deterministic carbon emission trading function
$HS(q_{h,s})$	Stochastic carbon emission trading function
L_h	Electric company's total deterministic generated electricity
$l_{h,s}$	Electric company's total stochastic generated electricity
Q_h	Electric company's total deterministic purchased renewable energy
$q_{h,s}$	Electric company's total stochastic purchased renewable energy
$R_{i,h}^{\pm}$	Deterministic storage charging/discharging rate
$r_{i,h,s}^{\pm}$	Storage charging/discharging rate in each scenario
$U(X_{i,h}, w_{i,h})$	Deterministic utility function
$U_s(x_{i,h,s}, x_{i,h,s}^{shed})$	Stochastic utility function
$X_{i,h}$	Households' deterministic demand
$x_{i,h,s}^{\pm}$	The maximum stochastic demand changes
$x_{i,h,s}^{shed}$	Load shedding
$Y_{i,h}$	Households' deterministic power sold to power grid
$y_{i,h,s}$	Households' stochastic power sold to power grid

I. Introduction

HOUSEHOLD subscribers make up an important portion of constant electricity consumers, and are electric companies' priority to provide with electricity. Installing photovoltaic (PV) systems has some drawbacks, like high level of capital demand, uncertainties of load and PV generation, and the lack of proper infrastructures for exchanging power and information in power grids, which discourages household customers from implementing the service. However, having less negative environmental impacts than traditional energy supplies may stimulate household customers to install PV systems.

Dynamic pricing is one of the most effective methods of pricing electricity energy, which can be utilized to expand renewable energy application. In this method, consumers' behavior and the amount of PV generation are taken into account so as to help them decide whether to sell, store, or consume the renewable energy. In addition, the data security of each side of the renewable energy market is another issue, which has to be addressed under different pricing mechanisms. As a result, presenting an efficient day-ahead dynamic pricing method can be an effective solution to expand the utilization of renewable energy resources in smart grids under various metering mechanisms.

The development of renewable energy resources requires policies and incentives, which were reviewed in [1]. These policies include private and public funds, various environmental taxes on carbon emission, and metering and pricing mechanisms [2]. Carbon emission taxes are policies that have direct effects on application of renewable energy resources in power grids [3], [4]. Reference [5] conducts an international review on the implementation of green electricity tariffs, considering data accuracy in different countries based on influential variables. Furthermore, introducing renewable energy resources to electricity market with various approaches needs adaptation policies [6].

Various government support schemes, e.g., feed-in-tariffs (FiTs), net metering, bidding process, are required to achieve the maximum penetration level of renewable energy resources in the Mediterranean region [7], [8]. However, combining European residential customers' electricity prices with funding costs in FiTs leads to the development of net metering [9]. As a result, it is required to compare the gained benefits of each of these mechanisms with each other, which is done in [10]. In [10], the benefits of FiTs and incentivized self-consumption schemes such as net metering and net billings are evaluated. Incentivized self-consumption schemes allow subscribers to consume generated renewable energy according to their monetary credits (net billing) and energy credits (net metering) [11], [12].

A comprehensive comparison among FiTs, net metering, and net purchase and sale is made in [13]. Electricity rates under each of these mechanisms are yielded based on customers' utility and social profits. However, the details of pricing mechanisms and their functions are not examined [13]. The economic aspects of FiTs, net metering, and net billing schemes are surveyed according to the accurate data of residential subscribers in Australian power grid in [14]. The results of this study include profitability index, internal rate of investment return, net present value, and discounted payback period in each scheme. Although the sensitivity and uncertainty of consumption and PV generation data are observed in the study, the details of retail rates are not considered [14].

Demand response programs are implemented to improve electricity consumption profile and enhance the reliability and efficiency of the process of providing electricity [15]. These programs are usually divided into two main categories: incentive-based and price-based programs [16]. Dynamic pricing is a price-based program, in which electricity prices are provided based on grid constraints in a particular period of time to derive demand responses [17], [18]. Reference [19] introduces an optimal dynamic pricing based on residential household demand response, in which customers are divided into two groups with or without smart metering. However, load uncertainty and data security are not considered in [19]. Reference [20] employs a customers' behavior learning machine to support a retailer. This method has a sufficient capability to model customer's behavior in the retail market, but the renewable energy participation and metering mechanisms are not studied [20].

Decomposition methods are suitable techniques for solving multi-area problems to ensure the security and privacy of each area [21], [22]. Accordingly, optimal conditional decomposition (OCD) technique has widespread usage in the electric market problems [23], [24]. Reference [25] introduces a dynamic pricing scheme by using Lagrangian relaxation method to decompose the electric company and residential customers. Reference [26] proposes an optimal day-ahead dynamic pricing for subscribers with renewable energy resources. Despite the detailed attention to the major factors of customers' behavior, utility profits, data security, and uncertainties of load and renewable energy are disregarded. In addition, the consideration of various metering mechanisms is the other aspect of pricing renewable energy resources, which is not taken to account [26].

There are various available techniques to model the uncertainty of parameters in the process of decision-making [27], [28]. The uncertainties of prices and PV generations for an optimal bidding strategy of residential management systems are modeled by interval-based models [29]. Reference [30] models the uncertainties of wind power production and market price with fuzzy scenario-based approaches. Reference [31] uses Monte Carlo methodology to solve a European multi-area market equilibrium [31]. To generate various scenarios for modeling the probabilistic nature of wind and PV generations, probability density functions are required in Monte Carlo methodology [32], [33]. Furthermore, a combination of fuzzy C-mean and roulette-wheel/Monte Carlo simulation is employed to model the electricity prices in scenario-based market [33]. In this regard, scenario reduction is required to reduce the number of computations [34].

Incorporating residential solar power in power grids requires studying different aspects of the subject. Mathematical modeling of customers' behavior, electric company's cost, and benefit functions is the initial step of the implementation of PV generations in power grids, which is observed in some previous studies [25]. Pricing strategies of PV electricity are of great importance depending on different metering mechanisms, however, which is the subject of the limited number of previous papers [13]. Moreover, despite the uncertain nature of PV power and customers' load, a few surveys implement stochastic decision-making algorithms for pricing mechanisms [14]. The privacy and security of residential customers and electric companies are other issues that are disregarded in some studies [26]. Consequently, the lack of a comprehensive study considering all these aspects of PV power pricing of residential customers is evident.

In this paper, day-ahead dynamic pricing in a power distribution system consisting of residential customers and electric companies is proposed. The residential customers are equipped with PV systems and battery storages. In addition, the power grid has sufficient infrastructures to buy back the residential solar power, and announce the day-ahead prices as well. The main purpose is to maximize the profits of customers and the electric company, and to minimize the power generation costs. The importance of security and data privacy of the electric company and customers is pursued by the OCD implementation. Therefore, the objective function of this study is divided into the decomposed customers' profit functions and the electric company's profit function. In addition, a Monte Carlo scenario-based technique is applied to model the uncertainty of PV generations and customers' demand. Metering mechanism is the other aspect of utilization of renewable energy resources in power grids. Accordingly, the main contributions of this paper can be briefly listed as follows.

1) The day-ahead dynamic pricing of renewable energy in a smart grid (consisting of household customers that are equipped with battery storages and PV systems, and an electric company) based on OCD method is optimized, while guaranteed the security and privacy of each side is guaran-

teed, and an optimal solution during a short time period is found.

2) The social welfare of residential customers and profit of electric company are maximized through minimizing production, storage, and carbon emission related cost functions and maximizing customers' utility functions.

3) A two-stage scenario-based decision-making procedure is implemented to cover the uncertainties of load and PV generation, in conjunction with modeling the residential consumers' preferences through a quadratic utility function.

4) An optimized day-ahead dynamic pricing of residential renewable energy is proposed under different metering mechanisms: FiTs, net metering, and net purchase and sale.

The remainder of this paper is as follows. Sections II and III describe the mathematical models of residential consumers and electric company, respectively. Section IV includes random variables for load and PV generation uncertainties, where the methods of scenario generation and reduction in stochastic decision-making are introduced. Section V contains a two-stage stochastic decision-making process of day-ahead dynamic pricing. Section VI elaborates the day-ahead dynamic pricing procedure through OCD method under various metering mechanisms. Section VII contains the numerical study of day-ahead dynamic pricing on a community consisting residential consumers and an electric company. Finally, conclusions are drawn in Section VIII.

II. Mathematical Model of Residential Costumers

In this paper, due to the presence of grid infrastructures for importing residential PV power, customers are active users who can decide to produce, consume, sell, or store solar electricity. This decision is made based on market prices of selling and purchasing electricity in conjunction with maintenance and operation costs. To model customer's objective function, formulating each of the equipment at the customer's place and its impact is required.

A. Storage

According to pollution increase caused by conventional electricity generation methods, energy storages have received much attention recently. The utilization of storage systems compensates for the uncertainty of PV products. The cost of operation and maintenance of a storage system depends on its charging and discharging rates, which is considered based on (1). In this regard, γ, δ, and θ are parameters that are considered according to the type of storage and its capacity range, in which γ is the constant cost of installing and maintenance of storage, δ is the operation cost, and θ is the rate of capacity [26].

$$DS(R_{i,h}^{\pm})=\delta(R_{i,h}^{+}+R_{i,h}^{-})^{2}+\gamma \tag{1}$$

The charging and discharging rates of the energy storage system, i.e., $R_{i,h}^{+}$ and $R_{i,h}^{-}$, are determined in (2) and (3), respectively, based on its total capacity. In addition, based on (4), the amount of stored power should not exceed its maximum capacity [35]. Due to the presence of both charging and discharging values in the cost function (1), they do not occur at the same time [36], [37].

$$R_{i}^{\max}=\theta B_{i}^{\max} \tag{2}$$

$$\begin{cases}0\le R_{i,h}^{+}\le R_{i}^{\max}\\0\le R_{i,h}^{-}\le R_{i}^{\max}\end{cases} \tag{3}$$

$$0\le\sum_{t=1}^{h}(R_{i,t}^{+}-R_{i,t}^{-})\le B_{i}^{\max} \tag{4}$$

B. PV System

The cost function of selling solar electricity to power grid is considered based on (5). According to (6), the amount of electricity sold to the power grid per hour should not exceed the PV system's production [14]

$$DR(Y_{i,h})=\sigma Y_{i,h} \tag{5}$$

$$0\le Y_{i,h}\le G_{i,h}-Y_{i,h} \tag{6}$$

C. Consumption

Lighting and electrical appliances make up the majority of residential consumers' demand, which are usually in a specific range based on (7).

$$X_{i,h}^{\min}\le X_{i,h}\le X_{i,h}^{\max} \tag{7}$$

D. Utility Function

Although each customer acts independently, the amount of required energy may depend on the factors such as time period, weather condition, and electricity price. Utility function is adopted to model different responses of customers to each of these factors. In general, a utility function is the level of a subscriber's satisfaction with the amount of electricity consumption and their preferences [25].

A utility function should be non-decreasing (users always want to consume more power) and concave (the level of costumers' satisfaction gradually gets saturated). In this regard, different models have been defined according to the properties of utility functions. In this paper, a quadratic model based on (8) is used, in which α is a predetermined factor [25]; and $w_{i,h}$ is a parameter that varies at different hours of the day for each subscriber [19], [38], [39].

$$U(x_{i,h},w_{i,h})=\begin{cases}w_{i,h}x_{i,h}^{k}-\alpha x_{i,h}^{k} & 0\le x_{i,h}^{k}\le\dfrac{w_{i,h}}{2\alpha}\\[2ex]\dfrac{w_{i,h}^{2}}{4\alpha} & x_{i,h}^{k}>\dfrac{w_{i,h}}{2\alpha}\end{cases} \tag{8}$$

III. Model of Electric Company

Electric companies must supply customers' electricity consumption, and the charging and discharging processes of storage system are based on (9). Furthermore, due to (10), the amount of produced electricity by companies should always cover the minimum and maximum customers' demands. The cost of providing required energy is calculated according to (11), which is a strictly convex function that increases in the offered energy capacity [25], [26].

$$\sum_{i}(X_{i,h}-Y_{i,h}+R_{i,h}^{+}-R_{i,h}^{-})\le L_{h} \tag{9}$$

$$L_{h}^{\min}\le L_{h}\le L_{h}^{\max} \tag{10}$$

$$C(L_{h})=aL_{h}^{2}+bL_{h}+c \tag{11}$$

In addition to supply customers' required electricity, the electric company can purchase an amount of green electricity from subscribers based on (12). Total amounts of green electricity are determined according to the specified amount of electricity energy included in their contracts based on (13). Besides, purchasing green electricity causes significant decrease in the amount of released pollution, which can be formulated as a mathematical function according to (14). In this regard, values m and n are derived from cost equilibriums, in which the amount of carbon emission is replaced by that of purchased renewable energy [25], [26].

$$\sum_h Q_h = T_{\max} \tag{12}$$

$$\sum_i Y_{i,h} = Q_h \tag{13}$$

$$H(Q_h) = -mQ_h^2 + nQ_h \tag{14}$$

IV. Random Variables

The uncertain nature of renewable energy resources requires special techniques for decision-making in power grids. In addition, the uncertainty of customers' demand has to be considered as well. As a result, the deterministic decision-making is not an appropriate solution, and it is necessary to consider the model uncertainties to achieve an accurate day-ahead dynamic pricing mechanism. In this regard, the uncertain input data of PV generations and customers' demand are modeled as random variables, which are presented as a set of scenarios with specific probabilities.

A. Scenario Generation

Defining a valid stochastic process requires a sufficient number of scenarios, so the primary data of PV generation and customers' demand are implemented as the root scenario in the Monte Carlo scenario generation method to generate other 1000 scenarios. In each scenario, random variables are generated with a standard deviation and a mean value according to their cumulative distribution function (normal distribution) [27].

B. Scenario Reduction

Based on the large number of generated scenarios and the importance of increasing the speed of solutions, scenario reduction methods are necessary. There are different scenario reduction methods, by which the overlap of scenarios is measured based on probabilistic criteria. Scenario reduction methods reduce the number of scenarios using Kantorovich distance matrix [40]. Kantorovich distance is the distance between the probability of two different scenarios, and its small size indicates two identical possible scenarios. In this case, the probability of all deleted scenarios is equal to zero, and the probability of new retained scenarios is equal to the sum of the previous probabilities and the probability of the closest deleted scenarios. In this study, forward selection method is used for scenario reduction, in which reduced scenario matrix is developed based on original scenario matrix. The selected scenarios in each iteration are the ones that minimize the Kantorovich distance between the reduced and original sets of scenarios. The process ends when a certain number of scenarios are achieved, or a certain Kantorovich distance is reached [41]-[43].

V. Two-stage Stochastic Decision-making Process

The uncertainty of day-ahead dynamic pricing is modelled by a two-stage stochastic programming, as shown in Fig. 1. In this vein, in the first stage of planning, deterministic decisions are made regardless of the numbers and the values of parameters in each scenario. In the second stage, the uncertainty of the program is modelled according to the value of variables in the previous stage, the number of scenarios, and the value of the parameters in scenarios. For example, in day-ahead dynamic pricing, the amount of PV generation and customers' demand are the variables of first stage of decision-making. However, the acceptable change limits of first-stage variables are specified based on the number of PV generation and customers' demand parameters in each scenario in the second stage [27].

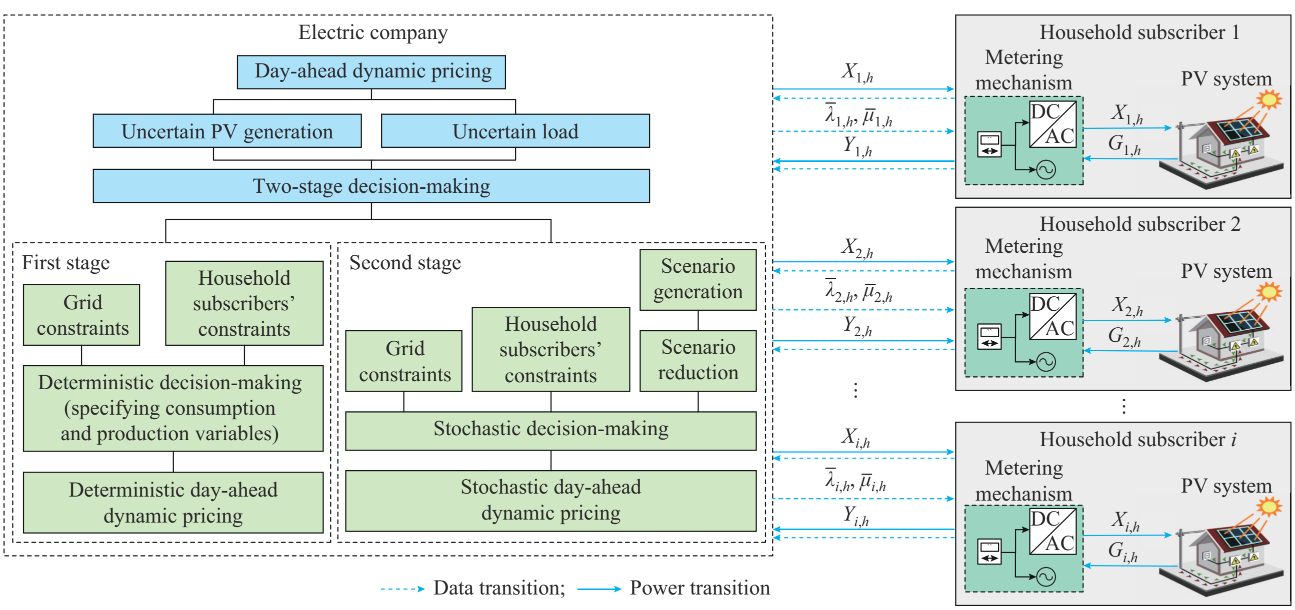

Fig. 1. Schematic diagram of proposed approach.

A. First Stage

In this stage, hourly decisions are made regardless of the amount of customers' demand and PV generation in each scenario. The amount of customers' demand, power sold to the grid, and PV generation are considered according to the grid constraints (1)-(14). These variables determine the value of objective function in the first stage of decision-making named social welfare, as expressed in (15) [26], [27]. Social welfare is the summation of profit and utility of consumers and the electric company's profit subtracted by the cost of purchasing and producing electricity.

$$Profit=\sum_h\left[\sum_i(U(X_{i,h})-DR(Y_{i,h})-DS(R^{\pm}_{i,h}))-C(L_h)+H(Q_h)\right] \tag{15}$$

B. Second Stage

In the second stage, variables are determined based on the number of available scenarios, the amount of customers' demand, PV generation parameters in each scenario, and the decision values in the first stage. Unlike the first stage of decision-making that takes place at the moment, the second-stage decisions are made after determining the random planning process. As a result, (16) - (20) are the linking constraints to illustrate the relation between the first- and second-stage values [27].

$$x_{i,h,s}=X_{i,h}-x^{-}_{i,h,s}+x^{+}_{i,h,s} \tag{16}$$

$$0\le x^{+}_{i,h,s}\le X^{+}_{i,h} \tag{17}$$

$$0\le x^{-}_{i,h,s}\le X^{-}_{i,h} \tag{18}$$

$$l_{h,s}\le L_h \tag{19}$$

$$q_{h,s}\le Q_h \tag{20}$$

Based on (16), the amount of customers' demand change in each scenario should include the difference between the first- and second-stage consumption amounts. In addition, the value of customers' demand changes, electric company's sold power, and purchased green power should be within specific ranges according to (17)-(20). The objective function (21) in the second stage of decision-making is the summation of social welfare function and the expected social welfare function in the first and second stages of decision-making, respectively. The corresponding values are determined based on constraints (1)-(20). The probability of each scenario π_s is equal to multiplication of probability of demand π_{demand} and PV generation scenarios π_{PV} [28].

$$\max\left\{\sum_h\left[\sum_i(U(X_{i,h})-DR(Y_{i,h})-DS(R^{\pm}_{i,h}))-C(L_h)+H(Q_h)\right]+\right.$$
$$\sum_s\pi_s\sum_h\left[\sum_i(U_s(x_{i,h,s},x^{shed}_{i,h,s})-DR_s(y_{i,h,s})-DS_s(r^{\pm}_{i,h,s}))+\right.$$
$$\left.\left.H_{h,s}(q_{h,s})-C_{h,s}(l_{h,s})\right]\right\} \tag{21}$$

VI. Day-ahead Dynamic Pricing Procedure

In the case of day-ahead dynamic pricing, it is required to guarantee the security and privacy of each side (company and residential customers) in conjunction with the load balance. The best approach in this situation is to consider separate solutions for the functions at each side [21]. As day-ahead dynamic pricing is a nonlinear programming, specific algorithms are required to decompose the objective function. Due to the presence of complex constraints (9) and (13), it is necessary to use the dual function of the main problem and solve it by dividing it into some separate sub-problems. Since complex constraints are shared between different sides and contain variables of electric company and residential customers, these constraints disrupt the process of solving the problem at each side, respectively. In the dual function, the complicated constraints of day-ahead dynamic pricing are replaced with dual variables λ, μ, λ_s, and μ_s. These dual variables are used to violate the complicated constraints of the primary problem, i. e., the hourly price of electricity. The OCD is a method for non-linear programs, which divides the main problem into a number of sub-problems according to the type of constraints, the number of subscribers, and electric companies, as shown in Fig. 2.

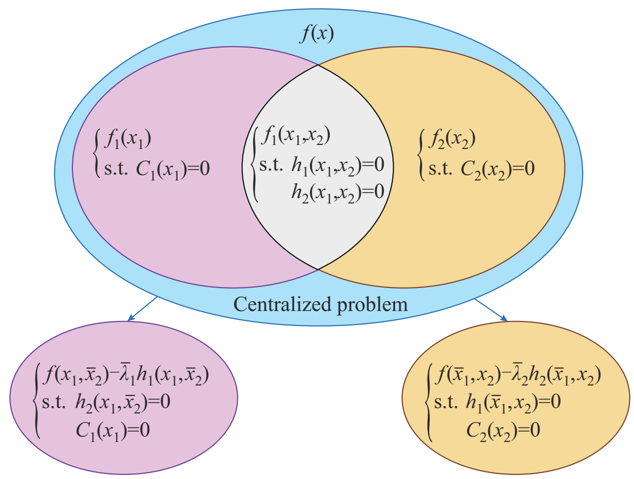

Fig. 2. Schematic description of OCD method.

A. Day-ahead Dynamic Pricing Under Various Metering Mechanisms

There are various metering mechanisms that enable residential customers to sell their green electricity to power grids. FiTs, net metering, and net purchase and sale are the main mechanisms to eliminate the gap between the retail market tariff and green electricity price. As common constraints in each of these metering mechanisms are different, the formulation of OCD method is defined separately in the following subsections.

1) FiTs

If subscribers choose FiTs mechanism to sell electricity to the power grid, they should sell a certain amount within a determined period at a specified price. Also, the subscriber's demand must be purchased from the power grid. In this case, the daily solar power of each subscriber $G_{i,g}$ is sold directly to the power grid according to (22), and load balance is guaranteed via (23) [1]. The cost of selling electricity to the power grid is based on (24). Due to the definite sale of green electricity to the power grid, there will be no need to store solar power [1], [8].

$$\sum_i G_{i,h} = Q_h \tag{22}$$

$$\sum_i (X_{i,h} - G_{i,h} + R^+_{i,h} - R^-_{i,h}) \le L_h \tag{23}$$

$$DR(G_{i,h}) = \sigma(G_{i,h}) \tag{24}$$

The objective functions of customers and electric company are defined as (25) and (26), respectively. According to these equations, all the electricity generated by solar resources is exported to the power grid at rates μ and $\mu_{h,s}$, respectively, in first and second stages of decision-making. The subscriber's required electricity is purchased at the prices of λ and $\lambda_{h,s}$ in the first and second stages of decision-making, repsectively [38].

$$\begin{aligned} Sub_1 = \sum_h \Bigg\{ & \sum_i (U(X_{i,h}) - DR(G_{i,h}) - DS(R^{\pm}_{i,h})) - \\ & \bar{\lambda}_h \left[\sum_i (X_{i,h} - G_{i,h} + R^+_{i,h} - R^-_{i,h}) - \bar{L}_h \right] + \bar{\mu}_h \left(\sum_i G_{i,h} - \bar{Q}_h \right) \Bigg\} + \\ & \sum_s \pi_s \Bigg\{ \sum_h \Bigg[\sum_i (U_s(x_{i,h,s}, x^{shed}_{i,h,s}) - DR_s(g_{i,h,s}) - DS_s(r^{\pm}_{i,h,s})) - \\ & \overline{\lambda s}_h \left[\sum_i (x_{i,h,s} - x^{shed}_{i,h,s} - g_{i,h,s} + r^+_{i,h,s} - r^-_{i,h,s}) - \bar{l}_{h,s} \right] - \\ & \overline{\mu s}_{h,s} \left(\sum_i g_{i,h,s} - \bar{q}_{h,s} \right) \Bigg] \Bigg\} \end{aligned} \tag{25}$$

$$\begin{aligned} Sub_2 = \sum_h \Bigg\{ & H(Q_h) - C(L_h) - \\ & \bar{\lambda}_h \left[\sum_i (\bar{X}_{i,h} - \bar{G}_{i,h} + \bar{R}^+_{i,h} - \bar{R}^-_{i,h}) - L_h \right] + \bar{\mu}_h \left(\sum_i \bar{G}_{i,h} - Q_h \right) \Bigg\} + \\ & \sum_s \pi_s \Bigg\{ \sum_h \Bigg[Hs_{h,s}(q_{h,s}) - Cs_{h,s}(l_{h,s}) - \\ & \overline{\lambda s}_{h,s} \left[\sum_i (\bar{x}_{i,h,s} - \bar{x}^{shed}_{i,h,s} - \bar{g}_{i,h,s} + \bar{r}^+_{i,h,s} - \bar{r}^-_{i,h,s}) - L_{h,s} \right] - \\ & \overline{\mu s}_{h,s} \left(\sum_i \bar{g}_{i,h,s} - q_{h,s} \right) \Bigg] \Bigg\} \end{aligned} \tag{26}$$

In the beginning of the day-ahead dynamic pricing, the initial prices are announced to the residential consumers. According to the prices, the customers send their responses to the electric company. Therefore, the electric company calculates the new prices for the next iteration. FiTs' day-ahead prices get updated in each iteration based on sub-gradient methods in (27)-(30). The parameter α^k is set to be $0.5/k$ to guarantee the convergence of day-ahead dynamic pricing.

$$\bar{\lambda}^{k+1}_h = \bar{\lambda}^k_h - \alpha \left[\sum_i (\bar{X}_{i,h} - \bar{G}_{i,h} + \bar{R}^+_{i,h} - \bar{R}^-_{i,h}) - L_h \right] \tag{27}$$

$$\bar{\mu}^{k+1}_h = \bar{\mu}^k_h - \alpha \left(\sum_i \bar{G}_{i,h} - \bar{Q}_h \right) \tag{28}$$

$$\overline{\lambda s}^{k+1}_{h,s} = \overline{\lambda s}^k_{h,s} - \alpha \left[\sum_i (\bar{x}_{i,h,s} - \bar{x}^{shed}_{i,h,s} - \bar{g}_{i,h,s} + \bar{r}^+_{i,h,s} - \bar{r}^-_{i,h,s}) - \bar{L}_{h,s} \right] \tag{29}$$

$$\overline{\mu s}^{k+1}_{h,s} = \overline{\mu s}^k_{h,s} - \alpha \left(\sum_i \bar{g}_{i,h,s} - \bar{q}_{h,s} \right) \tag{30}$$

2) Net Metering and Net Purchase and Sale Billing Mechanisms

In net metering and net purchase and sale mechanisms, the subscriber can consume or sell solar power to the power grid. Unlike FiTs, the subscriber can make a decision based on the electricity prices. The difference between net metering and net purchase and sale methods is in metering periods. Time slots in net metering are longer than those in net purchase and sale. Therefore, the production of the solar panel consists of two parts: power sold to the grid ($Go_{i,h}$) and power consumed by subscribers ($Gi_{i,h}$), as shown in (31), and load balance is considered in constraint (32). The cost of selling electricity to the power grid is calculated in (33) [1], [8].

$$G_{i,h} = Go_{i,h} + Gi_{i,h} \tag{31}$$

$$\sum_i (X_{i,h} - G_{i,h} + R^+_{i,h} - R^-_{i,h}) \le L_h \tag{32}$$

$$DR(Go_{i,h}) = \sigma(Go_{i,h}) \tag{33}$$

In (34), the consumer's profit is calculated under net metering and net purchase and sale mechanisms. In this regard, λ, μ, λ_s, and μ_s are the selling and purchasing prices, which are announced to the subscribers. As a result, the subscribers can make decisions about selling, consuming, and storing electricity.

$$\begin{aligned} Sub_1 = \sum_h \Bigg\{ & \sum_i (U(X_{i,h}) - DR(G_{i,h}) - DS(R^{\pm}_{i,h})) - \\ & \bar{\lambda}_h \left[\sum_i (X_{i,h} - G_{i,h} + R^+_{i,h} - R^-_{i,h}) - \bar{L}_h \right] + \bar{\mu}_h \left(\sum_i Go_{i,h} - \bar{Q}_h \right) \Bigg\} + \\ & \sum_s \pi_s \Bigg\{ \sum_h \Bigg[\sum_i (U_s(x_{i,h,s}, x^{shed}_{i,h,s}) - DR_s(g_{i,h,s}) - DS_s(r^{\pm}_{i,h,s})) - \\ & \overline{\lambda s}_h \left[\sum_i (x_{i,h,s} - x^{shed}_{i,h,s} - g_{i,h,s} + r^+_{i,h,s} - r^-_{i,h,s}) - \bar{l}_{h,s} \right] - \\ & \overline{\mu s}_{h,s} \left(\sum_i go_{i,h,s} - \bar{q}_{h,s} \right) \Bigg] \Bigg\} \end{aligned} \tag{34}$$

In net metering and net purchase and sale, the profit of the electric company is calculated based on (35). In this regard, the data of consumed, sold, and stored electricity considering the uncertainty of solar panel production and consumption are provided for the electric company. This aims to update the price values and makes them available to the subscribers to make next decisions. Price updates are based on (36)-(39) [8], [38].

$$\begin{aligned} Sub_2 = \sum_h \{ & H(Q_h) - C(L_h) - \bar{\lambda}_h \Bigg[\sum_i (\bar{X}_{i,h} - \bar{G}_{i,h} + \bar{R}^+_{i,h} - \bar{R}^-_{i,h}) - \\ & L_h \Bigg] + \bar{\mu}_h \left(\sum_i \overline{Go}_{i,h} - Q_h \right) \Bigg\} + \sum_s \pi_s \Bigg\{ \sum_h \Bigg[Hs_{h,s}(q_{h,s}) - \\ & Cs_{h,s}(l_{h,s}) - \overline{\lambda s}_{h,s} \Bigg[\sum_i (\bar{x}_{i,h,s} - \bar{x}^{shed}_{i,h,s} - \bar{g}_{i,h,s} + \bar{r}^+_{i,h,s} - \bar{r}^-_{i,h,s}) - \\ & L_{h,s} \Bigg] - \overline{\mu s}_{h,s} \left(\sum_i \bar{g}o_{i,h,s} - q_{h,s} \right) \Bigg] \Bigg\} \end{aligned} \tag{35}$$

$$\bar{\lambda}_h^{k+1} = \bar{\lambda}_h^k - \alpha\left[\sum_i (\bar{X}_{i,h} - \bar{G}_{i,h} + \bar{R}_{i,h}^{+} - \bar{R}_{i,h}^{-}) - L_h\right] \tag{36}$$

$$\bar{\mu}_h^{k+1} = \bar{\mu}_h^k - \alpha\left(\sum_i \overline{Go}_{i,h} - \bar{Q}_h\right) \tag{37}$$

$$\overline{\lambda s}_{h,s}^{k+1} = \overline{\lambda s}_{h,s}^{k} - \alpha\left[\sum_i (\bar{x}_{i,h,s} - \bar{x}_{i,h,s}^{shed} - \bar{g}_{i,h,s} + \bar{r}_{i,h,s}^{+} - \bar{r}_{i,h,s}^{-}) - \bar{L}_{h,s}\right] \tag{38}$$

$$\overline{\mu s}_{h,s}^{k+1} = \overline{\mu s}_{h,s}^{k} - \alpha\left(\sum_i \overline{go}_{i,h,s} - \bar{q}_{h,s}\right) \tag{39}$$

The implementation of renewable energy resources in power grids is a great environmental, strategic, and financial opportunity. Therefore, to move from a traditional power system to widespread application of renewable energy resources, new rules, patterns, and strategies are required. Various metering mechanisms and policies have been adopted to support the implementation of renewable energy resources in the recent studies [30]. In the following section, the day-ahead dynamic pricing in FiTs, net metering, and net purchase and sale is examined.

VII. Numerical Study

Day-ahead dynamic pricing is a bilateral process between residential consumers and electric companies due to the dependence of each side's profit on the specified price of exchanging electricity. In addition, due to the high cost of installing renewable energy resources, prices should stimulate required incentives for residential customers to invest in PV systems.

The simulated smart grid in this study consists of an electric company and 54 residential company with PV and storage systems. The consumption and PV generation data of residential consumers are based on an open-source Australian dataset called "solar home electricity data". As shown in Figs. 3 and 4, the data are from 54 randomly selected solar residential customers based on net billing mechanisms from July 1, 2010 to June 30, 2013 [44]. Accordingly, the preference parameter of each user w varies in [0.5, 6]. The maximum generation capacity of PV system for each customer is considered based on the maximum solar radiation in the customer's place and other related parameters. Moreover, the average generation cost of PV systems is 5 \$/kWh. The parameters of the cost and carbon emission profit function of the electric company and the customer's utility function [26] are set based on Table I. The normal distribution function of hourly residential consumption and PV generation data is used in the Monte Carlo method to construct uncertainty scenarios. In this case, 10000 scenarios are generated, which are reduced to 10 using the forward selection method to decrease the number of calculations.

In the following, the results of optimized day-ahead dynamic pricing are examined under different metering mechanisms. In addition, a two-stage decision-making process, which covers the uncertainty of demand and PV generation data, is also considered.

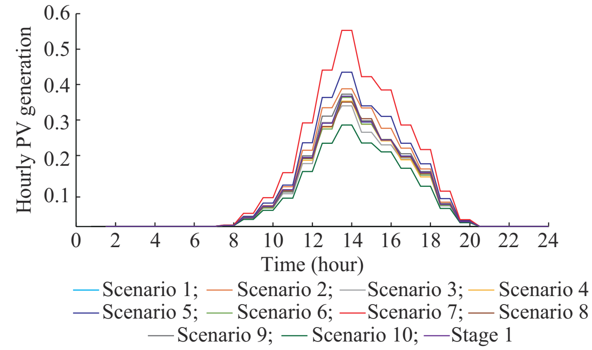

Fig. 3. Hourly PV generation in each scenario.

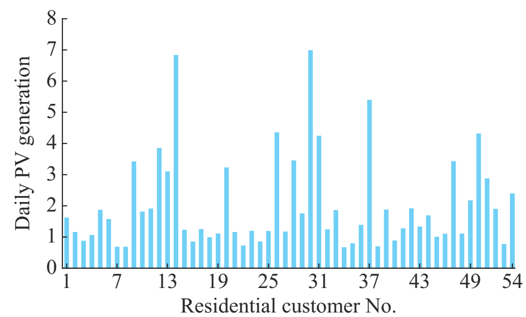

Fig. 4. Daily PV generation of 54 residential customers.

TABLE I
Parameters of Cost and Carbon Emission Profit Function

Parameter	Value	Parameter	Value
a	0.01	n	4
b	0	δ	0.1
c	0	α	0.1
m	0.001	w	[0.5, 6]

A. FiTs and Net Metering

In FiTs, according to the contracts, subscribers are obliged to sell all of their solar power and purchase their electricity demand. Since dynamic prices are announced day-ahead in this study, the period of contracts is set to be daily. Besides, in net metering, subscribers can decide to sell or consume their PV power. Therefore, they can sell their PV generation, or buy their consumption surplus at the end of the billing period. In the optimized day-ahead pricing under net metering, the period of contracts is considered to be daily, too. Table II shows the electricity prices of the electric company and PV generation in FiTs and net metering. According to the customers' preferences to consume their PV power in net metering, the renewable energy electricity prices are higher than those in FiTs. However, the electricity price of the electric company in FiTs is higher than that in net metering. The prices in net metering are adjusted to increase the costumers' incentives to sell their PV power to the power grid. The results demonstrate that the increase in the amount of PV generation causes reduction in the prices, according to the rise of the production.

TABLE II
ELECTRICITY PRICES OF ELECTRIC COMPANY AND PV GENERATION IN FITS AND NET METERING

Stage/ scenario	Electricity price in FiTs ($)		Electricity price in net metering ($)	
	PV generation	Electric company	PV generation	Electric company
Stage 1	1.15	6.909	1.15	6.58
Scenario 1	3.60	6.910	3.79	4.83
Scenario 2	3.24	7.600	3.41	4.81
Scenario 3	3.78	6.560	3.97	4.84
Scenario 4	3.74	6.630	3.94	4.83
Scenario 5	2.88	8.290	3.03	4.81
Scenario 6	3.78	6.770	3.98	4.82
Scenario 7	2.34	10.360	2.46	4.81
Scenario 8	3.60	6.910	3.79	4.81

B. Net Purchase and Sale

Net purchase and sale scheme is another version of net metering, in which the amount of consumption and PV power are compared in shorter time slots (hourly). Based on the average hourly consumption of 54 residential consumers, electricity prices in net purchase and sale are shown in Figs. 5 and 6. In order to lower the hourly amount of PV generation and costumers' consumption compared with FiTs and net metering mechanisms, the hourly electricity prices of the grid decrease. However, it causes higher PV power prices in comparison with the other two metering mechanisms according to the lack of green electricity. In this case, the higher prices stimulate costumers to sell their surplus PV generation.

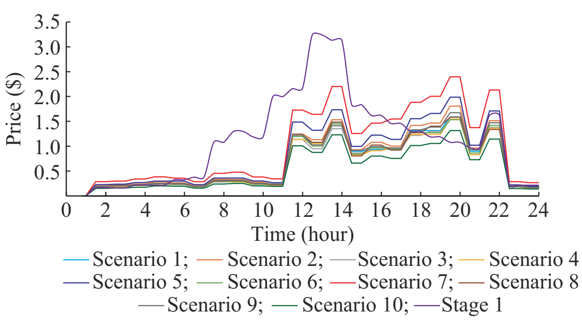

Fig. 5. Hourly electricity prices of PV generation in each scenario in net purchase and sale.

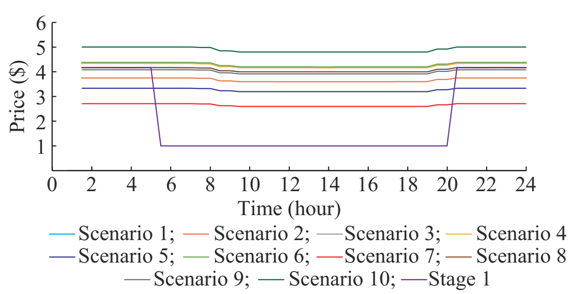

Fig. 6. Hourly electricity prices of electric company in each scenario in net purchase and sale.

It is the amount of electricity sold to the grid that makes each of these mechanisms different. In FiTs, 100% of customers sell all of their PV power to the grid according to their contracts. Besides, based on the cost of energy exchange, 98% of subscribers prefer to consume their PV power in net metering mechanism. However, as the demand of subscriber 51 is less than the PV generation, the surplus power is sold to the grid in each scenario. Supplying a part of costumers' demand from PV generations leads to a total load reduction, which happens in net metering, respectively and in net purchase and sale as shown in Fig. 7 and Table III.

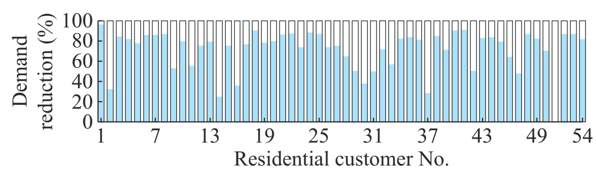

Fig. 7. Customers' demand reduction in net metering.

TABLE III
CUSTOMERS' DEMAND REDUCTION IN NET PURCHASE AND SALE

Time	Demand reduction (%)
8 p.m.-5 a.m.	0
6 a.m.	0.1
7 a.m.	0.9
8 a.m.	7.6
9 a.m.	19.9
10 a.m.	32.8
11 a.m.	11.9
12 a.m.	18.4
1 p.m.	17.3
2 p.m.	22.4
3 p.m.	17.1
4 p.m.	15.0
5 p.m.	9.0
6 p.m.	3.8
7 p.m.	0.7

In net metering and net purchase and sale, the average load reductions are about 28% and 11%, respectively. In this case, total load reduction is based on the capacity of PV system, which can be increased by battery storage implementation. As it is mentioned earlier in Section II, residential consumers are equipped with battery storage systems as well. However, storing process in FiTs and net metering stops due to the higher storage cost as a result of higher amount of charging/discharging rate. While in net purchase and sale, according to lower storage cost, the amount of charging/discharginge rate is based on Fig. 8. Charging process occurs during night hours when the electricity prices are low. Furthermore, discharging process happens during the PV generation hours. The battery storage functions independently from the PV system, and is connected directly to the power grid. Results show that the coordination of battery storage and PV systems at this scale requires storage cost reduction.

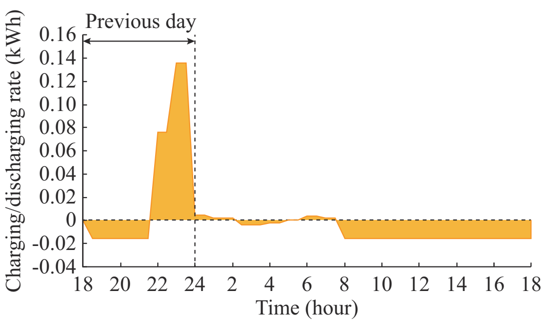

Fig. 8. Charging/discharginge rate in net purchase and sale.

Load shedding is one of electric company's approaches in stochastic decision-making to maximize the profits. In this case, load shedding varies according to the amount of customer's demand and PV generation. Generally, the customer's average daily demand is less than 8 kWh. As a result, the customers' utility function reduces based on their demand reduction. Therefore, increasing the capacity of PV systems and demand management can reduce the load shedding and increase the utility function.

VIII. Conclusion

In this study, the optimal day-ahead dynamic pricing under various metering mechanisms, i. e., FiTs, net metering, and net purchase and sale with the purpose of maximizing profits of customers and electric companies is proposed. The pricing mechanism is modelled in general algebraic modeling system (GAMS) as an integer convex non-linear program (using CONOPT solver), which depends on the amount of customers' demand, PV generation, and reactions to price changes. The results demonstrate that the profitability of day-ahead dynamic pricing among costumers, electric company, and society varies under each of the metering mechanisms. Among all mechanisms, the lowest and the highest prices for PV power and electricity take place in FiTs, which hold the highest social welfare, and only 40% of customers' satisfaction is rewarded. On the other hand, higher daily prices for PV generations in net metering results in approximately 70% of customers' satisfaction. In net purchase and sale, hourly day-ahead dynamic prices results in about 85% of electric company's satisfaction in conjunction with 11% load reduction. In addition, the maximum amount of carbon emission's profit (10.82% of social welfare) is obtained according to the highest amount of purchased green electricity from consumers in FiTs. However, according to customers' preferences to consume PV electricity rather than to sell it to the power grid, the amount of carbon emission's profit is not remarkable in net metering (0.4% of social welfare) and net purchase and sale (0.3% of social welfare). According to the results, the coordinate function of battery storage, electric vehicles, and PV systems can be studied in day-ahead dynamic pricing. Moreover, the customers' behavior and PV generation forecasting can be improved by implementing machine learning.

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