Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization

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***Abstract*—This paper proposes an optimal bidding strategy in the day-ahead market of a microgrid consisting of intermittent distributed generation (DG), storage, dispatchable DG, and price responsive loads. The microgrid coordinates the energy consumption or production of its components, and trades electricity in both day-ahead and real-time markets to minimize its operating cost as a single entity. The bidding problem is challenging due to a variety of uncertainties, including power output of intermittent DG, load variation, and day-ahead and real-time market prices. A hybrid stochastic/robust optimization model is proposed to minimize the expected net cost, i.e., expected total cost of operation minus total benefit of demand. This formulation can be solved by mixed-integer linear programming. The uncertain output of intermittent DG and day-ahead market price are modeled via scenarios based on forecast results, while a robust optimization is proposed to limit the unbalanced power in real-time market taking account of the uncertainty of real-time market price. Numerical simulations on a microgrid consisting of a wind turbine, a photovoltaic panel, a fuel cell, a micro-turbine, a diesel generator, a battery, and a responsive load show the advantage of stochastic optimization, as well as robust optimization.**

***Index Terms*—Market bidding strategy, microgrid, mixed-integer linear programming (MILP), robust optimization, stochastic optimization, uncertainty.**

NOMENCLATURE

The main symbols used in this paper are defined below. Others will be defined as required in the text.

Indices

i	Index of dispatchable generators, running from 1 to N_G.
j	Index of responsive demands, running from 1 to N_D.
s	Index of battery storage devices, running from 1 to N_S.
t	Index of time periods, running from 1 to N_T.
p	Index of stage 1 scenarios of day-ahead market prices, running from 1 to N_P.
w	Index of stage 2 scenarios of wind and photovoltaic (PV), running from 1 to N_W.
m	Index of energy blocks offered by generators (demand), running from 1 to N_I (N_J).

Variables

Binary Variables:

u_{ipwt}	1 if unit i is scheduled on in stage 1 scenario p stage 2 scenario w (scenario pw for the rest of this paper) during period t and 0 otherwise.
u_{jpwt}	1 if demand j is scheduled on in scenario pw during period t and 0 otherwise.
u^C_{kpwt}	1 if battery k is scheduled charging in scenario pw during period t and 0 otherwise.
u^D_{kpwt}	1 if battery k is scheduled discharging in scenario pw during period t and 0 otherwise.

Continuous Variables:

$p_{ipwt}(m)$	Power output scheduled from the mth block of energy offer by dispatchable unit i in scenario pw during period t. Limited to $p^{\max}_{it}(m)$.
$d_{jpwt}(m)$	Power consumption scheduled from the mth block of energy bid by demand j in scenario pw during period t. Limited to $d^{\max}_{jt}(m)$.
P_{ipwt}	Power output scheduled from dispatchable unit i in scenario pw during period t.
D_{jpwt}	Power consumption scheduled for demand j in scenario pw during period t.
P^A_{pt}	Purchased (if positive) or sold (if negative) power in the day-ahead market in scenario p during period t.
P^R_{pwt}	Purchased (if positive) or sold (if negative) power in the real-time market in scenario pw during period t.
λ^R_{pwt}	A random variable of real-time market price in scenario pw during period t.
P^C_{kpwt}	Charging power of battery k in scenario pw during period t.

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P^{D}_{kpwt}	Discharging power of battery k in scenario pw during period t.
SOC_{kpwt}	State of charge of battery k in scenario pw during period t.

Constants

$\lambda_{it}(m)$	Marginal cost of the mth block of energy offer by dispatchable unit i during period t.
$mc_{jt}(m)$	Marginal benefit of the mth block of energy bid by demand j during period t.
c_{kpwt}	Degradation cost of battery k in scenario pw during period t.
λ^{A}_{pt}	Day-ahead market price in scenario p during period t.
$\overline{\lambda}^{R}_{pwt}$	Expected real-time market price in scenario pw during period t.
δ_{pwt}	Deviation from the expected real-time market price in scenario pw during period t.
A_i	Operating cost of dispatchable unit i at the point of $P^{\min}_{i}$.
B_j	Consumption benefit of demand j at the point of $D^{\min}_{j}$.
$P^{\max}_{i}$	Maximum output of dispatchable unit i.
$P^{\min}_{i}$	Minimum output of dispatchable unit i.
$D^{\min}_{jt}$	Minimum power consumption of demand j during period t.
D^{F}_{jt}	Fixed component of demand j during period t.
Γ_{pw}	Control parameter of the robustness level during scenario pw.
π_p	Probability of scenario p.
π_w	Probability of scenario w.
P^{W}_{wt}	Wind turbine power output in scenario w during period t.
P^{P}_{wt}	PV power output in scenario w during period t.
$P^{C,\max}_{k}$	Maximum charging power of battery k.
$P^{D,\max}_{k}$	Maximum discharging power of battery k.
$\mathrm{SOC}^{\max}_{kt}$	Maximum SOC of battery k during period t.
$\mathrm{SOC}g^{\min}_{kt}$	Minimum SOC of battery k during period t.
η	Battery efficiency factor.
O_{pt}	Order of price scenario p during period t.

I. INTRODUCTION

THE INCREASING installation of distributed renewable and/or nonrenewable energy resources, emerging utility-scale energy storage, rapid growth of plug-in hybrid electric vehicles, and the maturing demand response in the distribution systems bring unprecedented opportunities and challenges to utilities, end users, manufacturers, and other participants in distribution system operations. A microgrid can be defined as a low voltage distribution network comprising various distributed generations (DGs), storage devices, and responsive loads that can be operated in both grid-connected and islanded modes [1]. From the point of view of the grid, a microgrid can be regarded as a controllable element which is connected to the main distribution network at the point of common coupling. Power may be imported from, or exported to the main distribution network under different market tariffs and microgrid operational conditions. In addition, a microgrid can provide ancillary services, such as, voltage support and regulation service, to the main distribution grid that a conventional end-user system cannot [2], [3]. From the point of view of customers, a microgrid cannot only provide energy, but also improve local reliability, reduce emissions and contribute to lower cost of energy supply by taking advantage of distributed energy resources (DERs), storage devices, and responsive loads [4]. Furthermore, a microgrid can improve power quality by supporting voltage and reducing voltage dips [5]. Due to such benefits, the microgrid has attracted growing attention from both academia and industry [6].

In order to fully achieve these benefits and supply energy in a reliable, economical, and environmentally friendly way, multiple DERs, storage devices, and responsive loads within the microgrid must be operated in a coordinated and coherent fashion. To that end, a scheduling system for the microgrid is fundamentally important. The scheduling system must consider forecasted output of renewable DG and demand, market tariffs or forecasted electricity and fuel prices and the technical constraints on devices so as to plan and schedule within the microgrid as well as the relationships with the main grid in terms of market participation. Considerable efforts have been devoted to optimal scheduling and management of microgrids [7]. In [8], a dynamic optimal scheduling method for a microgrid in grid-connected and islanded modes is proposed. The proposed method is based on dynamic programming combined with equal λ algorithm with a short time interval so as to consider the frequent fluctuation of renewable generation. In [9], an energy management system based on a rolling horizon strategy for a renewable-based microgrid is proposed. A mixed-integer optimization problem based on the latest updated forecast results is solved for each sliding window, and provides schedules for generators and responsive demands. A central controller based on mixed-integer linear programming (MILP) is developed to solve the optimal dispatch of an islanded microgrid in [10]. The cost of emissions is considered in [11].

In the above literature, the scheduling models are all built on deterministic optimization, which assumes a microgrid participates in the real-time market or is isolated. The forecast errors of renewable resources are neglected. However, the uncertainty of renewable energy is an important issue for economic and secure operation of a microgrid. For this reason, stochastic optimization and robust optimization, which can make informed decisions considering these uncertainties, has been proposed recently [12]–[14]. In [15], a day-ahead market bidding model for a virtual power plant (VPP) consisting of an intermittent source, a storage facility, and a dispatchable power plant is proposed. The bidding problem is formulated as a two-stage stochastic MILP model which maximizes the VPPs expected profit by selling and purchasing electricity in both day-ahead and balancing markets. The uncertain parameters, including the power output of the intermittent source and the market prices, are modeled via scenarios based upon historical data. However, the risk of lower expected profit is not considered. The reliability of fuel cells is considered in

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the scheduling of a microgrid by introducing stochastic programming in [16]. In [17], a robust optimization-based bidding strategy for the combination of wind farm and onsite storage in a deregulated electricity market is proposed. This bidding strategy takes account of uncertainty in both wind power forecasts and electricity price forecasts.

While [15]–[17] tackle the market bidding problem by either stochastic optimization or robust optimization, a unified stochastic and robust unit commitment model is proposed in [18]. This model can achieve a low expected total cost while ensuring system robustness by introducing weights for the components for the stochastic and robust parts in the objective function. In [19], a hybrid two-stage fuzzy-stochastic robust programming model is developed and applied to the planning of an air-quality management system. In the proposed model, some uncertainties are quantified as probability distribution functions, whereas the others are modeled by fuzzy membership functions. Various forms of uncertainties are incorporated within a general framework. In [20], a similar methodology is used to support an energy trading company to devise contracting strategies. These hybrid models leverage robust and stochastic optimization to achieve a low expected total cost while ensuring system robustness.

Another method of handling market bidding problem of flexible loads/generation, e.g., microgrid is by market redesign. In [21] and [22], a decision support algorithm and market participation policy for a load aggregator (LA) managing the charging of plug-in electric vehicles connecting at the same distribution network feeder is developed. As a prerequisite, a power market structure allowing for symmetric availability of information represented by the joint probability distribution of clearing prices conditional upon the current state of the system is assumed. In [23]–[25], a decentralized optimization of residential demand to minimize the cost to the utility company and customers while maintaining customer satisfaction is proposed. The modified market rules allow the market to clear and discover the socially optimal equilibrium prices. A distribution locational marginal price based market is proposed for a distribution network feeder in [26], the day-ahead market clearing prices and quantities for real and reactive power consumed/produced at each load/generation in the network are determined by minimizing distribution utility cost minus distributed participant utility subject to full ac load flow relations and voltage magnitude constraints. These methods are all involved with market redesign and policy changes, which are not likely to happen in the near term. For this reason, we propose a new microgrid bidding strategy, which can directly fit into the current Independent System Operator (ISO) market structure.

It should be noted that related bidding strategies have been proposed in the context of LAs. A stochastic linear programming model with scenarios for day-ahead and balancing market prices and load prediction errors is proposed for a small price taker agent's strategy [27]. The purchaser must arrange purchase for an uncertain demand that occurs the following day. Deviations from the day-ahead purchase are bought in a secondary market at a price that differs from the day-ahead price by virtue of regulating offers submitted by generators. A game-theoretic assessment of how a large buyer with market power should adapt to an electricity pool market with a day-ahead structure is found in [28]. In [29], the problem of optimal energy purchases in a deregulated California energy market is studied considering the uncertainties of demand and market prices. A stochastic dynamic optimization model with three sequential markets is formulated. In [30], the price volatility is explicitly considered in purchase allocation problems and the sequential nature is modeled by conditional stochastic characteristics. An analytical solution for the optimal allocation is derived with given demand and statistical characteristics of the market prices. A genetic algorithm based optimal bidding strategy for an electricity retailer who purchases power in the wholesale market and supplies it to end users is proposed in [31]. These efforts do not take into account distributed renewable resources. In [32], a day-ahead optimization process for LAs including dispatchable DG and distributed storage has been proposed assuming deterministic consumption profiles. The randomness of renewable sources is considered in [33] and the day-ahead bidding strategy is formulated as a generalized Nash equilibrium problem. Compared to these existing approaches, the proposed hybrid stochastic/robust optimization model in this paper aggregates adjacent loads (fixed and responsive loads), micro sources (wind turbine, PV panel, fuel cell, micro turbine, diesel generator, etc.) and energy storage (batteries) as a controllable cell and submits buying/selling bids into the day-ahead market. The uncertainties of renewable sources and market prices in both day-ahead and real-time horizon are considered explicitly. The flexibility of responsive demand and energy storage are also taken into consideration. To the best of our knowledge, no similar hybrid model for LA has been proposed in the literature.

The main contribution of this paper is to propose a new hybrid stochastic/robust optimization model for the microgrid bidding problem. The objective is to minimize the expected net cost, i.e., expected total cost of operation minus total benefit of demand. Since the buying prices for generation shortage in real-time market are usually higher than the day-ahead market prices, while the selling prices for generation surplus in real-time market are normally lower than the day-ahead market prices, microgrid should maximize its expected profit from trading in the day-ahead market, while minimizing as much as possible the need for resorting to the real-time market to amend its energy deviations. In addition, real-time market prices largely depend on unpredictable market conditions, making it difficult to capture its underlying stochastic process. For these reasons, the uncertain output of intermittent DG and day-ahead market price are modeled via scenarios based on forecast results, while a robust optimization is proposed to limit the power unbalance in real-time market taking account of the uncertainty of real-time market price. The proposed optimization model is solved by MILP and its outputs are hourly bidding curves to be submitted to the day-ahead market.

The rest of this paper is laid out as follows. In Section II, a bidding strategy based on pure stochastic programming is developed. Based on this model, robust optimization is introduced and the hybrid stochastic/robust optimization model is formulated in Section III. Results of numerical simulations on

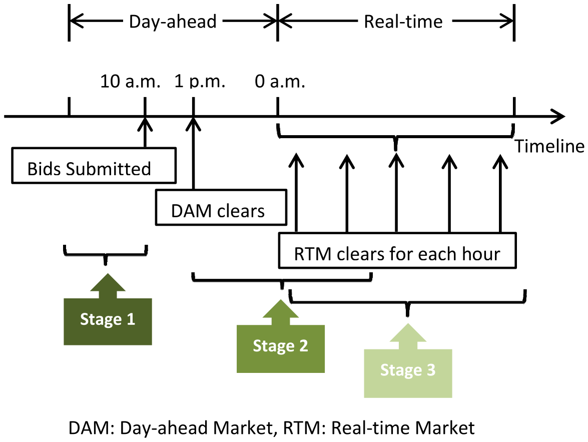

Fig. 1. Schematic of three stages.

a microgrid composed of a wind turbine, PV panel, fuel cell, micro-turbine, diesel generator, battery, and responsive load are presented in Section IV. Finally, the conclusion is given in Section V.

II. Bidding Strategy Based on Stochastic Optimization

This section describes a day-ahead market bidding strategy for microgrid based on pure stochastic optimization. The microgrid operator performs the stochastic optimization to determine the optimal production and consumption schedules of dispatchable generators and responsive loads, purchasing and selling electricity in the day-ahead market, as well as the charging and discharging schedules of the battery. The day-ahead and real-time market prices and power output of the intermittent sources, such as wind and PV are modeled via scenarios based on forecast results or historical scenarios. An effective scenario reduction method is essential for reducing the number of scenarios and the computational burden of the problem [34].

The optimization problem is formulated as a three-stage stochastic MILP problem. In the first stage, the microgrid submits bidding curves into day-ahead market before the day-ahead and real-time market prices and power output of the intermittent sources become known. In the second stage, the day-ahead market is cleared and the day-ahead market prices are assumed to be known. The power outputs of intermittent sources are realized by different scenarios right before the real-time market clearance at each hour. The microgrid schedules the production and consumption of dispatchable generators and responsive load as well as storage devices to guarantee feasible operation for each realization of the intermittent resources. This step happens before the real-time market is cleared. In the third stage, the real-time market price is realized, and the unbalanced power is absorbed by the real-time market. It should be noted that both day-ahead and real-time market prices are forecasted values based on historical data and other factors. The microgrid is generally a price-taker in the markets due to its limited capacity. A diagram of these three stages is shown in Fig. 1. The lighter color stages indicate decreasing uncertainty. Since the real-time market price will be known right after the uncertainties of intermittent resources are realized. It can also be understood as the uncertainties of intermittent resources realized in real-time, but before the real-time market prices become known. From this point of view, no decisions are made at stage three in the model and the three-stage model reduces to a two-stage stochastic optimization.

The objective function maximizes the expected benefit of the microgrid, or equivalently minimizes the expected net cost, which means expected total cost of operation minus total benefit of demand. It is formulated as follows:

$$\begin{aligned}\min \sum_{p=1}^{N_P} \pi_p \Bigg(& \sum_{t=1}^{N_T} \lambda_{pt}^A P_{pt}^A \\ & + \sum_{w=1}^{N_W} \pi_w \Bigg\{ \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} \sum_{m=1}^{N_I} \left[\lambda_{it}(m) p_{ipwt}(m) + A_i u_{ipwt} \right] \\ & - \sum_{t=1}^{N_T} \sum_{j=1}^{N_D} \sum_{m=1}^{N_J} \big[mc_{jt}(m) d_{jpwt}(m) \\ & \qquad + B_j u_{jpwt} \big] \\ & + \sum_{t=1}^{N_T} \sum_{k=1}^{N_S} c_{kpwt} \left(P_{kpwt}^D + P_{kpwt}^C \right) \\ & + \sum_{t=1}^{N_T} \sum_{i=1}^{N_G} S_{ipwt} \left(u_{ipwt}, u_{ipw,t-1} \right) \\ & + \sum_{t=1}^{N_T} E\left(\lambda_{pwt}^R \right) P_{pwt}^R \Bigg\} \Bigg). \end{aligned} \tag{1}$$

In the above formulation, the objective (1) is to minimize the expected net cost, including purchasing/selling electricity in the day-ahead market (line 1), production cost of dispatchable generators (line 2), minus benefit of responsive demand (line 3 [35]), battery degradation cost (line 4), startup cost of generators (line 5), and purchasing/selling electricity in the real-time market (line 6). The degradation cost of battery is estimated as a linear function of the battery charging/discharging power [36]. All terms are in mixed-integer linear form except the startup cost of generators (line 5), which can be recast into mixed-integer linear form as in [37]. The shutdown cost of generators can also be included similarly. They are neglected in this paper due to the small size of generators.

The objective function is subjected to the following constraints:

$$P_{ipwt} = \sum_{m=1}^{N_I} p_{ipwt}(m) + u_{ipwt} P_i^{\min} \quad \forall i, \forall t, \forall p, \forall w \tag{2}$$

$$D_{jpwt} = \sum_{m=1}^{N_J} d_{jpwt}(m) + u_{jpwt} D_{jt}^{\min} \quad \forall i, \forall t, \forall p, \forall w \tag{3}$$

$$0 \le p_{ipwt}(m) \le p_{it}^{\max}(m) \quad \forall i, \forall t, \forall p, \forall w, \forall m \tag{4}$$

$$0 \le d_{jpwt}(m) \le d_{jt}^{\max}(m) \quad \forall j, \forall t, \forall p, \forall w, \forall m \tag{5}$$

$$\begin{aligned} & \sum_{i=1}^{N_G} P_{ipwt} + P_{\mathrm{wt}}^W + P_{\mathrm{wt}}^P + P_{pt}^A + P_{pwt}^R + \sum_{k=1}^{N_S} P_{kpwt}^D \\ & - \sum_{i=1}^{N_S} P_{kpwt}^C = \sum_{j=1}^{N_D} \left(D_{jpwt} + D_{jt}^F \right) \quad \forall t, \forall p, \forall w \end{aligned} \tag{6}$$

$$u_{ipwt}P_i^{\min} \le P_{ipwt} \le u_{ipwt}P_i^{\max} \quad \forall i,\, \forall t,\, \forall p,\, \forall w \tag{7}$$

$$0 \le P_{kpwt}^C \le P_k^{C,\max} u_{kpwt}^C \quad \forall k,\, \forall t,\, \forall p,\, \forall w \tag{8}$$

$$0 \le P_{kpwt}^D \le P_k^{D,\max} u_{kpwt}^D \quad \forall k,\, \forall t,\, \forall p,\, \forall w \tag{9}$$

$$u_{kpwt}^C + u_{kpwt}^D \le 1 \quad \forall k,\, \forall t,\, \forall p,\, \forall w \tag{10}$$

$$\mathrm{SOC}_{kpwt} = \mathrm{SOC}_{kpw,t-1} + P_{kpwt}^C \eta - P_{kpwt}^D \frac{1}{\eta} \quad \forall k,\, \forall t,\, \forall p,\, \forall w \tag{11}$$

$$\mathrm{SOC}_{kt}^{\min} \le \mathrm{SOC}_{kpwt} \le \mathrm{SOC}_{kt}^{\max} \quad \forall k,\, \forall t,\, \forall p,\, \forall w \tag{12}$$

$$P_{pt}^A \le P_{p^\star t}^A \quad \forall t,\, \forall p,\, p^\star : O_{pt} + 1 = O_{p^\star t}. \tag{13}$$

Constraints (2) and (3) approximate the production cost of dispatchable generators by blocks [38], [39]. Similarly, the benefit of responsive demand is linearized and approximated by (4) and (5). The energy balance is enforced by (6). The total of the electricity produced by dispatchable generators, wind, PV, storage, and electricity purchased in day-ahead and real-time markets has to be equal to the amount of responsive demand and fixed demand in the microgrid. The output limits of dispatchable generators are defined by (7). The charging/discharging power limits of the battery are enforced by (8)–(10). The battery SOC is defined by (11) and the limit of SOC is enforced by (12). Constraint (13) ensures that the microgrid bidding curve is monotonously decreasing. O_{pt} denotes the order of price scenario p in each hour t. The price scenarios are ordered in each hour from the lowest price value to the highest one. Additionally, each unit or demand is subject to its own operating constraints, including minimum up and down time, initial condition, capacity limits, and ramp limits (see [40] for details about mathematical formulations of these constraints).

It should be noted that the network configuration of the microgrid is neglected in our proposed optimization model. We believe there are two justifications for this simplification. First, a microgrid practical size may be limited to a few MVA [1]. IEEE draft standard P1547.4 specifies an upper limit of 10 MVA [41]. Due to the limited capacity and the proximity of load and generation in a microgrid, the network is typically not the limiting constraint. Second, the network model greatly complicates the day-ahead bidding model without much likely benefit. Consideration of the network in the short-term or real-time horizon, where most of the uncertainties have been realized, strikes us as more appropriate [42].

III. Hybrid Stochastic/Robust Optimization

In this section, a hybrid stochastic/robust optimization model is proposed and formulated to minimize the expected net cost while limiting the unbalanced power in the real-time market and taking account of the uncertainty in real-time market price. The proposed model expands on the stochastic model in Section II.

We believe the proposed hybrid stochastic/robust optimization is preferable to pure stochastic optimization for two reasons. On the one hand, the proposed hybrid optimization model gives the microgrid operator an opportunity to choose different risk levels according to their system configuration and tolerance for risk. Given the high risks and the volatility in real-time pricing, the profitability and competitiveness of a microgrid may deteriorate rapidly by relying on the real-time market to mitigate deviations in energy needs [14]. Through the robust control parameter Γ, we can actually control the extent of uncertainty in real-time prices taken into account; thereby force the bidding strategy to be risk-preferred, risk-neutral, or risk-averse. On the other hand, the probability distribution of real-time market prices is not precisely known and may vary greatly with operating conditions. This probability distribution function is necessary for stochastic optimization, but not required for robust optimization. Therefore, instead of using the expected real-time market price $E(\lambda_{pwt}^R)$ as in (1), we propose a robust optimization counterpart to control the power imbalanced in the real-time market.

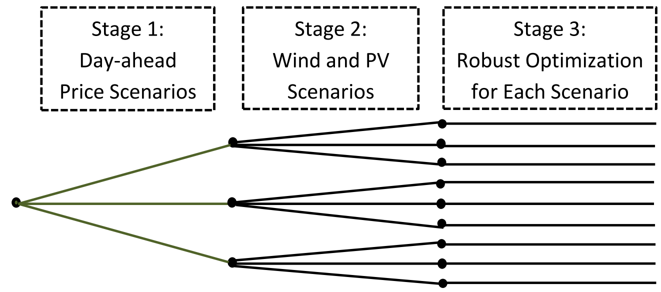

Fig. 2. Schematic of proposed hybrid stochastic/robust optimization.

Although the real-time price λ_{pwt}^R is hard to estimate and subject to large fluctuations as mentioned before, one can still determine some reasonable range for λ_{pwt}^R based on statistical data. Based on this range, each λ_{pwt}^R is modeled as an independent, symmetric and bounded random variable (with unknown distribution) which takes a value in $[\overline{\lambda}_{pwt}^R - \delta_{pwt},\, \overline{\lambda}_{pwt}^R + \delta_{pwt}]$ with $\delta_{pwt} \ge 0$.

To formulate the robust optimization counterpart, we introduce an integer control parameter Γ_{pw}, which takes values in the interval $[0,\, |J_{pw}|]$, where $J_{pw} = \{(pwt) \mid \delta_{pwt} \ge 0\}$, i.e., λ_{pwt}^R is subject to uncertainty for all $(pwt) \in J_{pw}$. The parameter Γ_{pw} controls the level of robustness in the objective. We are interested in finding an optimal solution that optimizes against all scenarios under which a number Γ_{pw} of real-time prices can vary in such a way as to maximally increase the objective function. If $\Gamma_{pw} = 0$, the uncertainty of real-time prices is completely ignored, while if $\Gamma_{pw} = |J_{pw}|$, all uncertainties in real-time prices are fully considered, leading to the most conservative solution [43].

The proposed robust counterpart of (1) is (14), as shown at the bottom of the next page, where microgrid has to purchase/sell balancing power in the real-time market at the highest/lowest real-time price. Thus, $\delta_{pwt}|P_{pwt}^R|$ can be interpreted as the penalty for resorting to the real-time market to mitigate its energy deviations. By maximizing this penalty, the worst scenario of real-time market price is found, and then this scenario is improved by the outer minimization.

By strong duality theory, the proposed hybrid stochastic/robust optimization can be recast as (15)–(20). A detailed description of how to convert the nonlinear objective

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function (14) into mixed-integer linear form as (15) can be found in the Appendix [13]. Variables Z_{pw} and q_{pwt} are dual variables of the inner level maximum optimization problem in (14) while y_{pwt} is an auxiliary variable used to obtain an equivalent linear expression

$$\begin{aligned}\min \quad & \sum_{p=1}^{N_P}\pi_p\Bigg(\sum_{t=1}^{N_T}\lambda_{pt}^{A}P_{pt}^{A}\\ &+\sum_{w=1}^{N_W}\pi_w\Bigg\{\sum_{t=1}^{N_T}\sum_{i=1}^{N_G}\sum_{m=1}^{N_I}\big[\lambda_{it}(m)p_{ipwt}(m)\\ &\qquad +A_i u_{ipwt}\big]\\ &-\sum_{t=1}^{N_T}\sum_{j=1}^{N_D}\sum_{m=1}^{N_J}\big[mc_{jt}(m)d_{jpwt}(m)\\ &\qquad + B_j u_{jtpwt}\big]\\ &+\sum_{t=1}^{N_T}\sum_{k=1}^{N_S}c_{kpwt}\Big(P_{kpwt}^{D}+P_{kpwt}^{C}\Big)\\ &+\sum_{t=1}^{NT}\sum_{i=1}^{NG}S_{ipwt}\big(u_{ipwt},u_{ipw,t-1}\big)\\ &+\sum_{t=1}^{N_T}\Big[\overline{\lambda}_{pwt}^{R}P_{pwt}^{R}+q_{pwt}\Big]\Bigg\}\\ &+Z_{pw}\Gamma_{pw}\Bigg)\end{aligned} \tag{15}$$

s.t. (2)–(13)

$$Z_{pw}+q_{pwt}\geq\delta_{pwt}y_{pwt}\quad\forall t,\ \forall p,\ \forall w \tag{16}$$

$$q_{pwt}\geq 0\quad\forall t,\ \forall p,\ \forall w \tag{17}$$

$$y_{pwt}\geq 0\quad\forall t,\ \forall p,\ \forall w \tag{18}$$

$$-y_{pwt}\leq P_{pwt}^{R}\leq y_{pwt}\quad\forall t,\ \forall p,\ \forall w \tag{19}$$

$$Z_{pw}\geq 0\quad\forall p,\ \forall w. \tag{20}$$

The schematic of proposed hybrid stochastic/robust optimization is shown in Fig. 2. The first stage takes account of the stochasticity of day-ahead market price. The variables in this stage are the buying or selling quantities under different day-ahead market price scenarios. These price-quantity pairs will form the basis for the bidding curves for each hour. The stochasticity of wind and PV is introduced in the second stage. The variables in this stage include the unit status and output of dispatchable units, consumption of responsive load and charging or discharging power of battery. The third stage ensures the result is robust to uncertain real-time price for each scenario. The variables at this stage are the unbalanced power across all scenarios. Note that all these variables are linked through the power balance equality constraint (6) which unifies the three stages into a single optimization problem.

TABLE I
PARAMETERS OF DISPATCHABLE GENERATORS

Unit Type	Min. Power (kW)	Max. Power (kW)	Startup Cost ($)	Operating Cost $(a+bP+cP^2)$		
				a	b	c
Diesel	20	60	3	1.30	0.0304	0.00104
Microturbine	10	30	2	0.40	0.0397	0.00051
Fuel Cell	10	30	1.5	0.38	0.0267	0.00024

IV. CASE STUDIES

A. Test System Data

The proposed hybrid stochastic/robust optimization model is demonstrated on the modified Oak Ridge National Laboratory (ORNL) Distributed Energy Control and Communication (DECC) Laboratory microgrid test system as shown in Fig. 3. The modified system includes various DERs, including a wind turbine, PV panel, fuel cell, microturbine, diesel generator, and battery. The parameters for the dispatchable generators are shown in Table I [44]. For simplicity, the quadratic cost curves are converted into three-piece piece-wise linear cost curves. Due to the small capacity of resources, the minimum up and down time as well as the ramping rates are neglected.

The 60 kW wind turbine model is from [45]. Based on the wind speed forecast result, 15 wind speed scenarios are generated and the corresponding wind generation power outputs are calculated and shown in Fig. 4. The generation cost of a wind turbine is assumed to be zero. The 60 kW PV model is from [46]. The solar irradiance and temperature data is measured data from [47]. The standard deviations of forecast errors of solar irradiance and temperature are assumed to be 10% and 3%, respectively. Fifteen scenarios of solar irradiance and temperature are generated and the corresponding PV output power is calculated. The capacity of the battery is 50 kWh with a maximum charging/discharging power of 25 kW. The battery efficiency is assumed to be 0.9.

The analysis is conducted for a 24-h scheduling horizon and each time interval is set to be 1 h. The forecast total demand and day-ahead market prices are shown in Table II [44]. The demand forecast error is neglected for simplicity since it can

$$\begin{aligned}\min \sum_{p=1}^{N_P}\pi_p\Bigg(&\sum_{t=1}^{N_T}\lambda_{pt}^{\mathrm{A}}P_{pt}^{A}+\sum_{w=1}^{N_W}\pi_w\Bigg\{\sum_{t=1}^{N_T}\sum_{i=1}^{N_G}\sum_{m=1}^{N_I}\big[\lambda_{it}(m)p_{ipwt}(m)+A_i u_{ipwt}\big]-\sum_{t=1}^{N_T}\sum_{j=1}^{N_D}\sum_{m=1}^{N_J}\big[mc_{jt}(m)d_{jpwt}(m)+B_j u_{jpwt}\big]\\ &+\sum_{t=1}^{N_T}\sum_{i=1}^{N_G}S_{ipwt}\big(u_{ipwt},u_{ipw,t-1}\big)+\sum_{t=1}^{N_T}\sum_{k=1}^{N_S}c_{kpwt}\Big(P_{kpwt}^{D}+P_{kpwt}^{C}\Big)\\ &+\sum_{t=1}^{N_T}\overline{\lambda}_{pwt}^{\mathrm{R}}P_{pwt}^{R}+\max_{\{S_{pw}|S_{pw}\subseteq J_{pw},\left|S_{pw}\right|\leq\left|\Gamma_{pw}\right|\}}\sum_{t\in S_{pw}}\delta_{pwt}\left|P_{pwt}^{R}\right|\Bigg\}\Bigg)\end{aligned} \tag{14}$$

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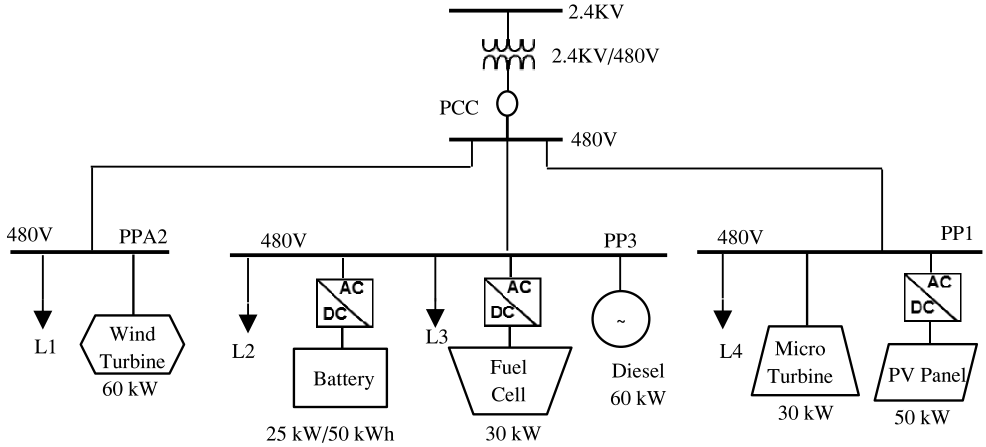

Fig. 3. Modified ORNL DECC microgrid test system.

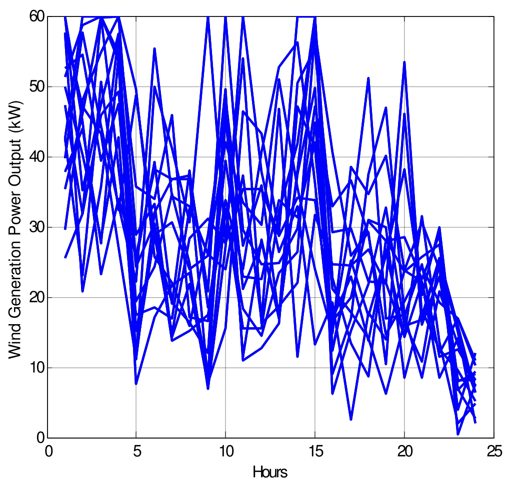

Fig. 4. Fifteen wind power scenarios.

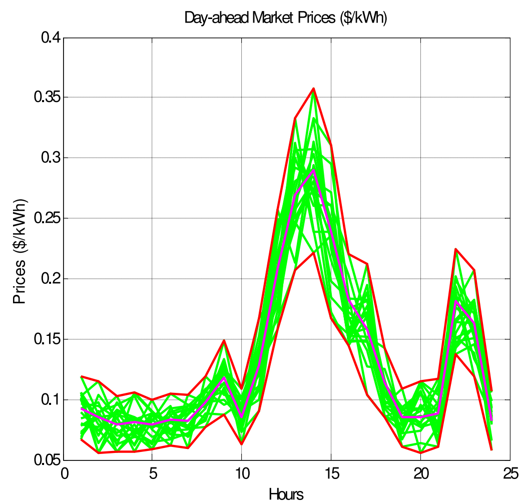

Fig. 5. Twenty day-ahead market price scenarios.

TABLE II
FORECAST LOAD AND DAY-AHEAD MARKET PRICES

Hour	Load (kW)	Price (ct/kWh)	Hour	Load (kW)	Price (ct/kWh)
1	221.0000	8.65	13	336.7000	26.82
2	219.7000	8.11	14	331.5000	27.35
3	224.9000	8.25	15	340.6000	13.81
4	221.0000	8.10	16	344.5000	17.31
5	227.5000	8.14	17	331.5000	16.42
6	240.5000	8.13	18	328.9000	9.83
7	260.0000	8.34	19	325.0000	8.63
8	315.9000	9.35	20	331.5000	8.87
9	330.2000	12.0	21	338.0000	8.35
10	338.0000	9.19	22	322.4000	16.44
11	347.1000	12.3	23	296.0000	16.19
12	336.7000	20.7	24	239.2000	8.87

be folded into other uncertainty. The standard deviation of day-ahead market price forecast error is assumed to be 10%. Twenty scenarios of day-ahead market prices are generated as shown in Fig. 5. The magenta line is the average of the red envelope.

Demand is divided into two parts: 1) fixed; and 2) price elastic with a proportion of 80% and 20%, respectively. The price elasticity is set at 0.001 cent/kW^{2}h. The maximum and minimum price responsive demand is set to be 100 and 0 kW, respectively. Based on these parameters, the benefit function of responsive demand is calculated, and then linearized into three-piece piece-wise linear segments. All numerical simulations are coded in MATLAB and solved using the MILP solver CPLEX 12.2. With a prespecified duality gap of 0.1%, the running time of each case is about 5 min on a 2.66 GHz Windows-based PC with 4 GB of RAM.

B. Microgrid Bidding Curves in the Day-Ahead Market

The bidding curves of microgrid in the day-ahead market for selected hours are shown in Fig. 6. As can be seen, the bidding quantity decreases as the market price increases for all hours. Comparing the bidding curves between different hours, at high price hours, such as hour 14, the bidding quantities are small, but with high bidding prices. While at low price hours, such as hours 2 and 20, the bidding quantities are large, but with low bidding prices. This indicates that during high price hours, the microgrid increases the output power of dispatchable units and discharges power from the battery, while during low price hours, the microgrid reduces its output and charges the battery. In this way, the operating cost is minimized.

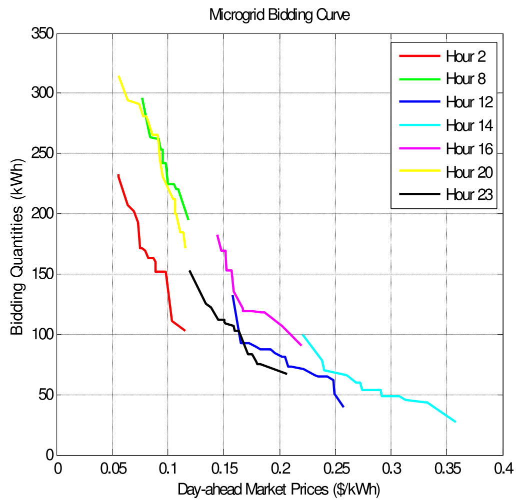

Fig. 6. Microgrid bidding curves for selected hours.

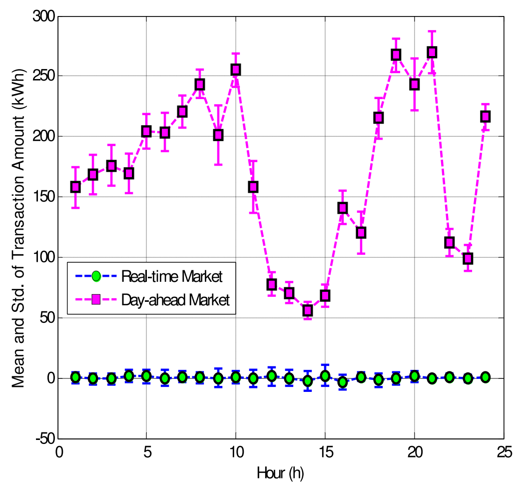

Fig. 7. Transaction amount in day-ahead and real-time market with microgrid bidding in day-ahead market.

C. Comparison of Results With and Without Microgrid Bidding in the Day-Ahead Market

The expectation and standard deviation of transaction amounts in the day-ahead market and real-time market are shown in Fig. 7. The vertical bars show the standard deviations and the marks on each bar shows the expectations for transaction amounts. By participating in the day-ahead market, the microgrid obtains most of the energy from the day-ahead market, while the unbalanced power in real-time market is very small in both expectation and standard deviation. As a comparison, the transaction amount of microgrid in day-ahead and real-time market without bidding in day-ahead market is shown in Fig. 8. As can be seen, the microgrid gets less energy from the main grid when it can only get energy from real-time market. This is because the microgrid can only purchase energy at a higher price than the day-ahead market price with $\Gamma_{pw} = 24$ for all p and w. In this situation, the microgrid increases its self-production to reduce the cost. By bidding into the day-ahead market, the expected cost is reduced from \$361.4 to \$237.5 (about 34.28%). The benefits of microgrid

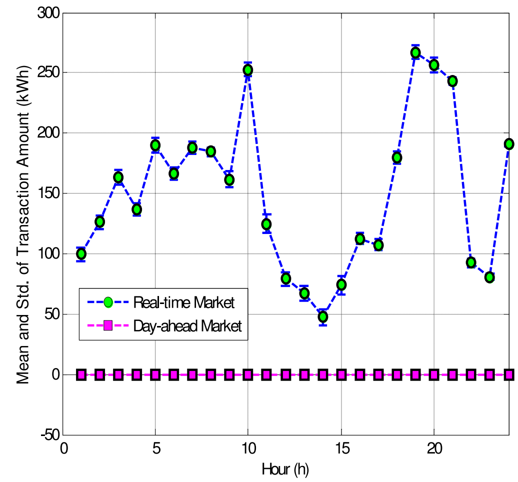

Fig. 8. Transaction amount in day-ahead and real-time market without microgrid bidding in day-ahead market.

TABLE III
VSS of Day-Ahead Market Price and Wind and PV

Stochastic solution (\$)	Expected cost of using deterministic day-ahead market price solution (\$)	VSS of day-ahead market price (\$)
237.5099	243.1398	5.6839 (2.39%)
Stochastic solution (\$)	Expected cost of using deterministic wind and PV solution (\$)	VSS of wind&PV (\$)
237.5099	239.0697	1.5598(0.66%)

bidding in the day-ahead market are twofold. First, the microgrid reduces its economic risk by obtaining most of the energy it imports from the day-ahead market instead of real-time market. Second, a lower real-time balancing capacity is needed for the utility or ISO.

D. Calculation of the Value of Stochastic Solution

To show the advantage of stochastic optimization over deterministic optimization (which can be found by replacing corresponding random variables by their expected values), we calculate the value of stochastic solution (VSS). First, we replace corresponding random variables by their expected values and solve the deterministic optimization. Second, we test this deterministic solution with the possible scenarios of the random variables and find the expected cost of using the deterministic solution. This expected cost measures how well the deterministic solution performs. The difference between this expected cost and stochastic solution is the VSS. As shown in Table III, considering the stochasticity of the day-ahead market price reduces the expected operating cost of the microgrid by 2.39%. Similarly, considering the stochasticity of wind and PV output, the expected operating cost of microgrid is reduced by 0.66%.

E. Effect of Robust Optimization

A robust formulation is proposed in this paper to limit the unbalanced power in real-time market. In order to show the effect of robust control parameter Γ_{pw}, we assume all $\Gamma_{pw} = \Gamma$

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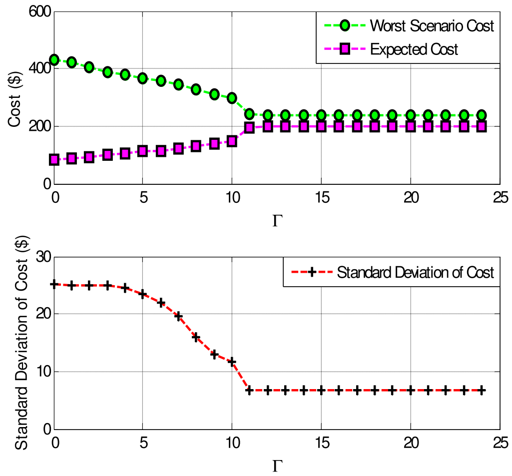

Fig. 9. Effect of robust control parameter Γ.

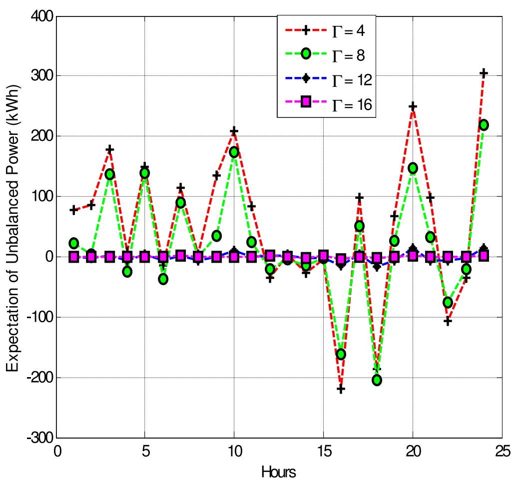

Fig. 10. Expectation of unbalanced power in real-time market with different Γ.

without loss of generality and calculate the bidding curves for different values of Γ. Then, we test these bidding curves with possible scenarios of real-time market prices and find the expected costs of these bidding curves calculated with various values of Γ. Twenty scenarios of real-time market prices are generated using a normal distribution. The generated real-time market prices has the same expectation as the day-ahead prices, but higher standard deviation (15%). The worst scenario costs and expected costs with different Γ are shown in Fig. 9. As Γ increases, the expected cost monotonically increases with Γ, while both cost of worst scenario and standard deviation of cost decrease, i.e., the more robust the solution, the higher the expected cost. This indicates the tradeoff between risk and benefit. In order to show the effect of Γ on unbalanced power in the real-time market, the expectations and standard deviations of unbalanced power in real-time market with different Γ are shown in Figs. 10 and 11. With higher Γ, both expectation and standard deviation of unbalanced power in real-time market decrease, the economic risk is reduced and the solution becomes more robust. This gives the microgrid operator an opportunity to choose different risk levels according to their system configuration and tolerance for risk.

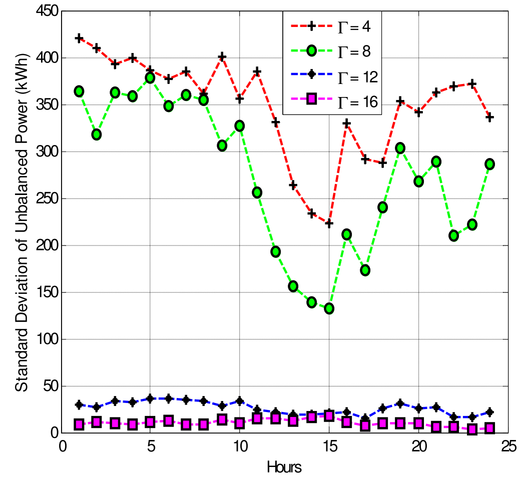

Fig. 11. Standard deviation of unbalanced power in real-time market with different Γ.

V. Conclusion

In this paper, a new bidding strategy for a microgrid in the day-ahead market based on a hybrid stochastic/robust optimization is proposed. The uncertain output of intermittent DG and the day-ahead market price are modeled via scenarios based on forecasts, while a robust optimization is proposed to limit the unbalanced power in real-time market taking account of the uncertainty in the real-time market price. Compared to a pure stochastic optimization model, the proposed hybrid model is robust against uncertain real-time market price by limiting the unbalanced power in the real-time market. Numerical simulations on a microgrid composed of a wind turbine, PV panel, fuel cell, micro-turbine, diesel generator, battery, and responsive load show the advantage of stochastic optimization as well as robust optimization. In particular, the proposed hybrid stochastic/robust optimization model links the unbalanced power in real-time market with a robust control parameter. In other words, by selecting different values for the robust control parameter, the microgrid operator can choose different risk levels according to their system configuration.

Appendix

Derivation of Robust Objective Function (15)

Since only the last term of (14) is nonlinear, we need to convert it into mixed-integer linear form. The last term of (14) can be expressed as

$$\beta = \max_{\{S_{pw}|S_{pw}\subseteq J_{pw},|S_{pw}|\le|\Gamma_{pw}|\}} \sum_{t\in S_{pw}} \delta_{pwt}\left|P^R_{pwt}\right|$$
$$= \max\left\{\sum_{t\in J_{pw}} \delta_{pwt}\left|P^R_{pwt}\right| z_{pwt} : \sum_{t\in J_{pw}} z_{pwt} \le \Gamma_{pw},\right.$$
$$\left. 0\le z_{pwt}\le 1,\ \forall t\in J_{pw}\right\}. \tag{21}$$

By the property of strong duality, we can formulate the dual problem of (21) as (22), where Z_{pw} is the dual variable of constraint $\sum_{t \in J_{pw}} z_{pwt} \leq \Gamma_{pw}$, q_{pwt} is the dual variable of constraint $z_{pwt} \leq 1$, and y_{pwt} is auxiliary variable used to obtain equivalent linear expression

$$\beta = \min \left\{ \sum_{t \in J_{pw}} q_{pwt} + Z_{pw}\Gamma_{pw} : q_{pwt} \geq 0,\ Z_{pw} \geq 0, \right.$$
$$\left. Z_{pw} + q_{pwt} \geq \delta_{pwt} \left| P^R_{pwt} \right|,\ \forall t \in J_{pw} \right\}$$
$$= \min \left\{ \sum_{t \in J_{pw}} q_{pwt} + Z_{pw}\Gamma_{pw} : q_{pwt} \geq 0,\ Z_{pw} \geq 0, \right.$$
$$Z_{pw} + q_{pwt} \geq \delta_{pwt} y_{pwt},\ y_{pwt} \geq 0$$
$$\left. -\ y_{pwt} \leq P^R_{pwt} \leq y_{pwt},\ \forall t \in J_{pw} \right\}. \tag{22}$$

Assume all λ^R_{pwt} are subject to uncertainty, substitute (22) into (14), we obtain the objective function of robust UC in mixed-integer linear form as (15).

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