Block Coordinate Decent Robust Bidding Strategy of a Solar Photovoltaic coupled Energy Storage System operating in a Day-ahead Market

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***Abstract*—This paper presents a two-stage adaptive robust optimization approach to develop an optimal bidding strategy for a grid-connected solar photovoltaic (PV) plant with a coupled energy storage system (ESS). This study models the power flow through system elements as well as the exact interactions between the system and upstream network. The uncertainties of solar radiation, affecting the PV generation and market prices are characterized by bounded intervals in polyhedral uncertainty sets. A robust optimization is formed as a min-max-min problem characterizing both "here-and-now" and "wait-and-see" variables. This tri-level robust optimization is solved through a decomposition approach, where it is recast into a min master problem and a max-min subproblem. Unlike previous conventional robust optimization models, that utilise duality for solving the inner subproblem, a block coordinate decent (BCD) methodology is used in this study. Accordingly, instead of conducting duality theory, the subproblem is solved over a first-order Taylor series approximation of uncertainties. This results in a moderate computation/mathematical burden. Moreover, there is no need to linearize the dualized problem anymore, as no duality is conducted. Using BCD methodology in solving the robust optimization model also allows modelling binary variables as recourse actions, which differentiates this approach to conventional dual-based robust optimization models. An illustrative example is provided to demonstrate the performance of the proposed bidding strategy model.**

Keywords—Robust optimization, bidding strategy, energy management, energy storage, electricity market.

NOMENCLATURE

A. Indices

t	Index of hour.

B. Parameters

δ_t^-	Penalty rate for surplus of power.
δ_t^+	Penalty rate for shortage of power.
P_t^{pv-gen}	Generated power by PV plant.
η^{chg}	Charging efficiency of the ESS.
η^{dis}	Discharging efficiency of the ESS.
E^{int}	Initial state of charge (SoC) of the ESS.
E^l	Steady-state loss of charge of the ESS in each hour.
P_{min}^{chg}	Minimum permissible charge rate of the ESS.
P_{max}^{chg}	Maximum permissible charging rate of the ESS.
P_{max}^{dis}	Maximum permissible charge rate of the ESS.
P_{min}^{dis}	Minimum permissible discharge rate of the ESS.
E_{min}	Minimum permissible SoC of the ESS.
E_{max}	Maximum permissible SoC of the ESS.
P_{min}^{in}	Minimum allowable buying bid.
P_{max}^{in}	Maximum allowable buying bid.
P_{max}^{out}	Maximum allowable selling bid.
P_{min}^{out}	Minimum allowable selling bid.
Ψ	Uncertainty budget.
π_t	Market price.
$\bar{\pi}_t$	Forecast of market price.
$\bar{P}_t^{pv-gen}$	Forecast of PV generation.
$\hat{\pi}_t^{dev+}$	Maximum positive deviation of uncertain market price.
$\hat{\pi}_t^{dev-}$	Maximum negative deviation of uncertain market price.
$\hat{P}_t^{dev+}$	Maximum positive deviation of uncertain PV generation.
$\hat{P}_t^{dev-}$	Maximum negative deviation of uncertain PV generation.

C. Variables

P_t^{pv}	PV power sold to network.
α_t^+	Binary variable indicating surplus of power.
α_t^-	Binary variable indicating shortage of power.
P_t^{n-chg}	Charging power of the ESS provided by network in buying bids.
P_t^{dis}	Charging power of the ESS.
π_t^{dev+}	Positive deviation of uncertain market price.
π_t^{dev-}	Negative deviation of uncertain market price.
$\tilde{\pi}_t$	Uncertain market price.
P_t^{chg}	Charge power of the ESS.
P_t^{pv-chg}	Charge power of the ESS, provided by PV plant.
$\tilde{P}_t^{pv-gen}$	Uncertain PV generation.
P_t^{dev+}	Positive deviation of uncertain PV generation.
P_t^{dev-}	Negative deviation of uncertain PV generation.
E_t	SoC of the ESS.
x_t^{chg}	Charging status of the ESS (binary variable).
x_t^{dis}	Discharging status of the ESS (binary variable).
x_t^{in}	Buying status in bidding strategy (binary variable).
x_t^{out}	Selling status in bidding strategy (binary variable).

D. Sets

Ξ^T	Set of time slots.
Ξ^I	Set of first-stage variables.
Ξ^{II}	Set of second-stage variables.
Ξ^{US}	Set of uncertain parameters.
Ξ^{UP}	Set of uncertain PV generation.
$\Xi^{U\pi}$	Set of uncertain market price.

E. Vectors and matrices

$\boldsymbol{A}, \boldsymbol{F}$	Coefficient matrices of objective function.
$\boldsymbol{B}, \boldsymbol{C}, \boldsymbol{E}, \boldsymbol{G}, \boldsymbol{H}/\boldsymbol{D}$	Coefficient/requirement vectors.
$\overline{\boldsymbol{U}}/\boldsymbol{U}^{dev+}$	Vector of estimated/deviated uncertain parameters.
$\widetilde{\boldsymbol{U}}$	Vector of uncertain parameters.
$\boldsymbol{X}/\boldsymbol{Y}$	Vector of start-up/operation variables.

I. Introduction

A. Problem Description

The accelerating uptake of distributed energy systems, including solar and battery systems, in electricity distribution networks has resulted in significant technical and operational issues such as voltage/frequency deviation, reverse power flow, etc. Moreover, intermittency in solar photovoltaic (PV) generation, which is mostly due to atmospheric conditions, has made the operation of these systems challenging. This becomes more vital if the PV system has been installed for benefiting recovery schemes such as a bidding strategy. In a bidding strategy, for instance, any deviation from the submitted bids, i.e., shortage/surplus, of a PV plant results in extra costs which is not favorable for such a system. To manage this risk, energy storage systems (ESSs) such as batteries, are often deployed in conjunction with PV systems. ESS can also be beneficial for the upstream network as it can provide arbitrage opportunities for meeting network constraints more efficiently.

Although an ESS can increase the efficiency of PV plants as well as providing support for the upstream network, the short-term volatile nature of solar power is still an important factor in operating these systems, especially in a competitive market. This issue becomes of major importance when developing a bidding strategy for day-ahead markets, using forecasts of solar radiation and market prices. As such, a rigorous approach is needed to characterize the uncertainties in these forecasts and how this impacts optimal operation of these systems.

B. Literature Survey

The accelerating uptake of energy storage systems, such as battery systems, has seen significant interest in optimizing the operation of these systems in power and energy networks [1]. The arbitrage ability of an ESS allows provide opportunities where lower cost energy can be purchased from network or generated energy stored and subsequently sold into the network at times of high prices. Therefore, the optimal operation of PV plants and ESSs is strongly dependent on the uncertainty of electricity market prices [2]. Recent work has investigated self-scheduling and bidding strategies of ESSs under uncertainties. In [3] the bidding strategy of a merchant compressed air energy storage (CAES) was developed through information-gap theory to characterize the uncertainty of electricity price. The bidding strategy of a battery energy storage system (BESS) was investigated in [4].

A stochastic programming (SP) approach was developed in [5] to characterize the uncertainties for the bidding strategy of an ESS operating within the electricity market. Although SP is a more efficient method in uncertainty characterization, compared to deterministic and probabilistic methods, it is subject to a huge number of uncertainty scenarios which is not practical. To void this issue, the backward scenario reduction method has been used by [6] to reduce the simulation time. While scenario reduction methodologies are able to reduce the optimization computational time, SP is still subject to the lack of tractability as it requires *a priori* knowledge of the distributions of uncertain parameters. This requirement is not practical for real world studies. Moreover, SP can be intractable if the number of uncertain parameters is high. This becomes more vital as more resolution is required is uncertain parameters [7]. There is also a possibility of ending up with non-optimal or non-feasible solution if there is significant deviation between the uncertain parameters and the forecasted uncertainties which were considered in the SP model at the first place [8].

To overcome the issues associated with SP models, robust optimization (RO) approaches have are widely utilised in order to characterize the associated uncertainties [9]. The benefit of RO, compared to SP, is that it is the worst-case realization of uncertainties that are modelled. This process is done by modelling the uncertainties through polyhedral sets where RO decides each uncertain parameter should reach its maximum value in order to maximize the worst-case realization of uncertainties [10-11]. This means any uncertainty realization in real situation will be less than the worst-case realizations resulting in a feasible solution in any condition. This is why RO solutions are more reliable than SP and scenario-based models. However, this may seem a little conservative as it is not much realistic to simulate all uncertainties by their worst-case realization. To cope with this problem, post-event analysis or after the fact analysis has been conducted in some RO studies to reduce their conservativeness.

Conventional RO models use duality theory in order to solve the max-min subproblem by changing it into a single-level max problem. This is because it is not possible to directly solve the max-min subproblem as it is a two-level problem. Duality theory allows the transformation of the two-level problem into a single-level problem. The operation of a wind farm, coupled with an ESS, as well as its upstream network interactions through optimal bidding strategy was developed through RO in [12]. However, the buying/selling bidding status of the plant, which was determined by binary variables was replaced by a sell-only bidding strategy as no binary variable was considered, in the max-min subproblem. This is because duality theory was used in the model of [12]. A similar approach was utilized in [13] for a wind generation coupled ESS to develop a robust model predictive control-based bidding strategy. The model of [13] only implemented a single-stage max-min problem. A similar approach to [12] was also taken in [14] to simplify the use of the duality theory approach for solving the max-min subproblem.

It deserves mentioning that the use of duality theory results in not having binary variables in the sub-problem. In particular, the binary variables are removed or obtained in the master problem before uncertainty realizations. Accordingly, the binary variables such as storage charging/discharging status are obtained without considering the uncertainties. Therefore, the arbitrage ability of the storage is not exploited to compensate the effects of uncertain parameters. Therefore, further studies are required to characterize binary variables in the sub-problem after uncertainty realizations.

C. Contributions

In this paper, a recourse-based robust bidding strategy is proposed for a solar PV coupled ESS operating in a day-ahead market. A tri-level min-max-min RO problem is developed which recasts into a single-level min master problem and a bi-level max-min subproblem through a decomposition using column-and-constraint (C&C) methodology.

In the literature survey, the use of duality theory was seen to limit the application of RO in terms of characterizing binary variables after uncertainty realizations. This is because the dual of a mixed-integer model is generally weak, intractable and complicated [15]. By contrast, this paper utilized a block coordinate decent (BCD) approach to eliminate this limitation. In particular, BCD builds the second-stage subproblem by a first-order Taylor series approximation of the min subproblem which is conducted to minimize the objective function over uncertain parameters. This provides the opportunity to iteratively solve the max-min subproblem without the duality theory technique.

Note that the iterative BCD methodology is conducted in each iteration of the C&C methodology. This means the BCD robust model in this paper includes two nested loops, namely outer loop (for the C&C methodology) and the inner loop (for the BCD technique). This proposed model is called "BCD robust", for the remainder of this paper.

Using BCD robust model, the obtained solutions are more reliable than the solutions from SP. They are also feasible as long as the uncertain parameters are deviating between the polyhedral uncertainty sets.

D. Paper organization

The remainder of this paper is organized as follows. A deterministic bidding strategy for a PV coupled ESS is proposed and discussed in Section II. In Section III, the BCD robust optimization model as well as its solution algorithm is developed and discussed. Simulation results are provided in Section IV and conclusions presented in Section V.

II. Deterministic Day-ahead Bidding Strategy for the PV-ESS System

In this section, a deterministic model is developed for a coupled PV-ESS system which includes both internal self-scheduling of the system as well as its optimal interactions with upstream market. Note that, the deterministic model (1), neglects the uncertainties. The associated uncertainties are characterized and modelled in Section III.

The deterministic model is developed as (1) and is based on the given system configuration in Fig. 1.

$$\text{Min} \overbrace{\sum_{t\in\Xi^T} -\left(P_t^{pv} + \alpha_t^+ \cdot \delta_t^- - \alpha_t^- \cdot \delta_t^+\right)\cdot \pi_t}^{\mathbb{M}1= PV\ bid\ and\ shortage/surplus\ rates} + \overbrace{\sum_{t\in\Xi^T}\left(P_t^{n-chg} - P_t^{dis}\right)\cdot\pi_t}^{\mathbb{M}2= BESS\ buying/selling\ bid} \quad (1a)$$

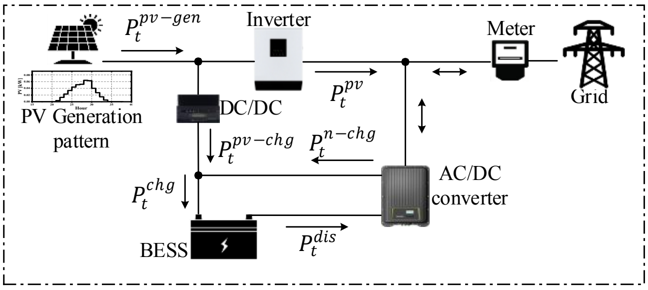

Fig. 1. Configuration of the considered system

s.t.

AC/DC Power flow constraints:

$$P_t^{chg} = P_t^{n-chg} + P_t^{pv-chg};\ \forall t \in \Xi^T \quad (1b)$$

$$P_t^{pv-gen} = P_t^{pv} + P_t^{pv-chg};\ \forall t \in \Xi^T \quad (1c)$$

ESS constraints:

$$E_t = E_{t-1} + \left(P_t^{chg}\cdot\eta^{chg} - P_t^{dis}\cdot\frac{1}{\eta^{dis}}\right)\cdot\Delta t - E^l;\ \forall t \in \Xi^T \quad (1d)$$

$$\sum_{t\in\Xi^T}\left(P_t^{chg}\cdot\eta^{chg} - P_t^{dis}\cdot\frac{1}{\eta^{dis}}\right) = E^l \cdot T; \quad (1e)$$

$$E_{t=0} = E^{int}; \quad (1f)$$

$$P_{min}^{chg}\cdot x_t^{chg} \le P_t^{chg} \le P_{max}^{chg}\cdot x_t^{chg};\ \forall t \in \Xi^T \quad (1g)$$

$$P_{min}^{dis}\cdot x_t^{dis} \le P_t^{dis} \le P_{max}^{dis}\cdot x_t^{dis};\ \forall t \in \Xi^T \quad (1h)$$

$$E_{min} \le E_{dt} \le E_{max};\ \forall t \in \Xi^T \quad (1i)$$

$$x_t^{chg} + x_t^{dis} \le 1;\ \forall t \in \Xi^T \quad (1j)$$

Upstream network interaction constraints:

$$P_{min}^{in}\cdot x_t^{in} \le P_t^{n-chg} \le P_{max}^{in}\cdot x_t^{in};\ \forall t \in \Xi^T \quad (1k)$$

$$P_{min}^{out}\cdot x_t^{out} \le P_t^{pv} + P_t^{dis} \le P_{max}^{out}\cdot x_t^{out};\ \forall t \in \Xi^T \quad (1l)$$

$$x_{dt}^{in} + x_{dt}^{out} \le 1;\ \forall t \in \Xi^T \quad (1m)$$

The objective function in (1a) includes two terms. The term $\mathbb{M}1$ includes the selling bid of the PV plant as well as out-of-bid penalty allocations. In particular, PV plant is penalized if it deviates from the submitted bids. Therefore, penalty rates δ_t^- and δ_t^+ are added to the surplus and shortage portion of the bis, respectively. These values are considered as pre-contracted parameters. For example, in Iran, values of δ_t^- and δ_t^+ are 0.9 and 1.1, respectively. This means that if more power is available in a certain bidding period, the surplus of power is sold to the network with 90% of the market price, and if less power is available, the shortage is penalized by 110% of the market price. The second term of the objective function, i.e., $\mathbb{M}2$, includes buying and selling bids of the ESS. In fact, the ESS can be charged by both the PV plant and the upstream network when in charging mode.

Constraints (1b) and (1c) are the power flow equations for the considered configuration in Fig. 1. ESS operating constraints are given by (1d)-(1j). Constraint (1d) represents the dynamic energy balance of the battery system while (1e) is the end-coupling constraint of the battery, i.e., it makes sure the ESS has been charged to its initial point at the end of the operating horizon. The initial energy level of the ESS is given by (1f). Constraints (1g)-(1i) represent the allowable ranges for charging, discharging, and energy level of the battery.

Constraint (1j) makes sure that the ESS is working in one mode only, i.e., out-of-use, charging, or discharging. Upstream network power trading constraints are given by (1k)-(1m). Constraints (1k)-(1l) are the allowable ranges of buying/selling power from/to the network while (1m), making sure that only one of the buying or selling statuses are in place.

In fact, according to (1m) the PV-ESS plant can only bid for buying or selling at each bidding period.

As it is seen in (1), the associated uncertainties with PV generation and market prices are ignored. Therefore, the obtained solutions of the model in (1) may not be practical if uncertainties arise. In the next section, the BCD robust model is presented and discussed.

III. BCD Robust Bidding Strategy for the PV-ESS System

A. Two-stage Robust Model

In joint planning and operation studies, the planning variables are considered as “here-and-now” variables, while the operating variables are considered as “wait-and-see” variables. This is because the planning decisions are taken for the long-term performance of the system and are independent on short-term uncertainties, while the operating decisions must be taken under uncertainties as they are strongly subject to change if uncertainties arise.

Considering the above explanation of "here-and-now" and "wait-and-see" decision variables, the RO problem is formed as the tri-level min-max-min problem given by (2).

$$\min_{X\in\Xi^{I}}\left(\boldsymbol{A}'\cdot\boldsymbol{X}+\max_{\widetilde{U}\in\Xi^{US}}\min_{Y\in\Xi^{II}}\boldsymbol{F}',\boldsymbol{Y}\right) \tag{2a}$$
s.t.
$$\Xi^{I}=\{\boldsymbol{X}\in\{\boldsymbol{0},\boldsymbol{1}\}^{N_X}\ |\ \boldsymbol{CX}\geq\boldsymbol{D}\} \tag{2b}$$
$$\Xi^{II}=\{\boldsymbol{Y}\in\mathbb{R}^{N_Y}\ |\ \boldsymbol{E}(\boldsymbol{X},\boldsymbol{Y},\widetilde{\boldsymbol{U}})\geq 0\} \tag{2c}$$
$$\Xi^{US}=\{\widetilde{\boldsymbol{U}}\in\mathbb{R}^{N_{\widetilde{U}}}\ |\ \widetilde{\boldsymbol{U}}=\overline{\boldsymbol{U}}\pm\boldsymbol{U}^{dev\pm}\} \tag{2d}$$

In (2a), the outer min problem minimizes the term $\boldsymbol{A}'\cdot\boldsymbol{X}$ over "here-and-now" variables denoted by vector $\boldsymbol{X}$. The outer min problem is subject to constraint (2b) which represents the set of constraints including "here-and-now" variables. The inner min problem in (2a) minimizes the term $\boldsymbol{F}',\boldsymbol{Y}$ over "wait-and-see" variables, while the inner max problem maximizes it over the uncertain parameters. (2c) represents the set of the remaining constraints which are dependent on "wait-and-see" variables, while the inner max problem is subject to uncertainty set realizations as (2d).

B. Uncertainty Set Realization

The extended form of the uncertainty set realizations is given by (3), which characterizes the uncertainties of both PV generation and market price.

$$\Xi^{UP}=\{\tilde{P}_t^{pv-gen}=\bar{P}_t^{pv-gen}+P_t^{dev+}-P_t^{dev-};\ \forall t\in\Xi^{T}\} \tag{3a}$$
$$\Xi^{U\pi}=\{\tilde{\pi}_t=\bar{\pi}_t+\pi_t^{dev+}-\pi_t^{dev-};\ \forall t\in\Xi^{T}\} \tag{3b}$$
$$0\leq P_t^{dev+}\leq\hat{P}_t^{dev+};\forall t\in\Xi^{T} \tag{3c}$$
$$0\leq P_t^{dev-}\leq\hat{P}_t^{dev-};\forall t\in\Xi^{T} \tag{3d}$$
$$0\leq \pi_t^{dev+}\leq\hat{\pi}_t^{dev+};\forall t\in\Xi^{T} \tag{3e}$$
$$0\leq \pi_t^{dev-}\leq\hat{\pi}_t^{dev-};\forall t\in\Xi^{T} \tag{3f}$$
$$\Xi^{US}=\left\{\Xi^{UP}\cup\Xi^{U\pi},\sum_{t\in\Xi^{T}}\left|\frac{P_t^{dev+}}{\hat{P}_t^{dev+}}+\frac{P_t^{dev-}}{\hat{P}_t^{dev-}}\right|+\sum_{t\in\Xi^{T}}\left|\frac{\pi_t^{dev+}}{\hat{\pi}_t^{dev+}}+\frac{\pi_t^{dev-}}{\hat{\pi}_t^{dev-}}\right|\leq\Psi\right\}; \tag{3g}$$

Since the RO problem in (2) is a min-max-min problem, it cannot be directly solved. To solve such a problem, a decomposition algorithm is conducted by means of the well-known column-and-constraint generation methodology [1]. This solving procedure is consistent with RO models in other energy systems [13-17].

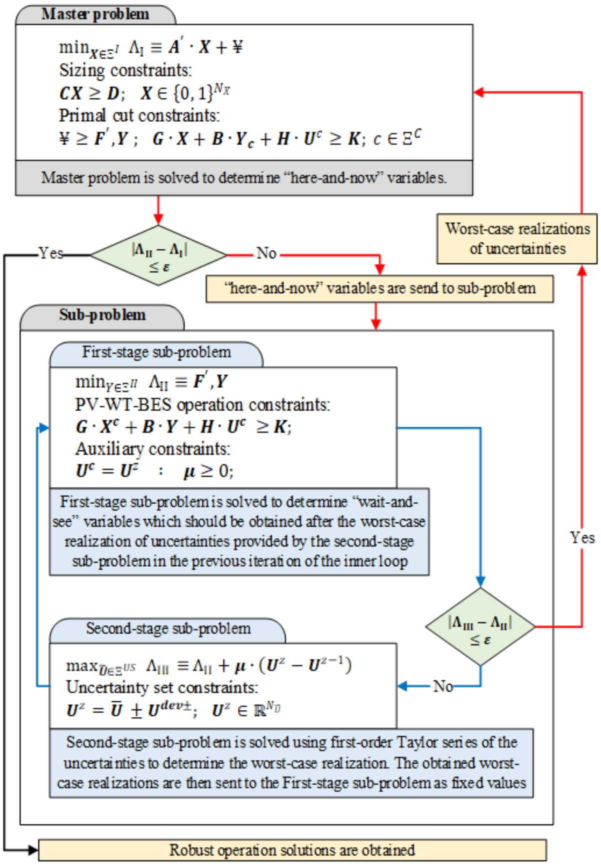

Fig. 2. Outline of the algorithm in solving BCD Robust model

The decomposition methodology recasts the min-max-min problem as a single-level min master problem (the outer min problem in (2a)) and a bi-level max-min subproblem (the inner max-min problem in (2a)). The subproblem itself is also solved by the block coordinate decent (BCD) methodology instead of duality theory, specifically it is is solved with a first-order Taylor series approximation over uncertainty sets, instead of using duality theory. This results in breaking the bi-level subproblem into two single-level subproblems.

C. BCD Robust Approach and its Solution Methodology

Unlike [10-14], the sub-problem in this study is not solved by duality theory as the block coordinate decent methodology is used instead. In the BCD technique, the max-min sub-problem is recast into two individual subproblems, with a first-stage min subproblem followed by a second-stage max subproblem. The second-stage sub-problem is built upon the firs-order Taylor series of the fist-stage sub-problem considering uncertain parameters resulting in the maximum value of objective function through the worst-case realization of uncertainties. The obtained worst-case realization of uncertainties in the second-stage sub-problem is then fixed in the first-stage sub-problem to obtain the “wait-and-see” variables. Therefore, the solution methodology of the BCD robust optimization problem includes two nested loops.

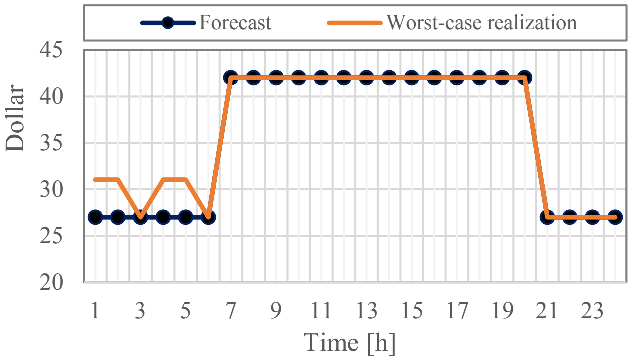

Fig. 3. Worst-case realization of market price

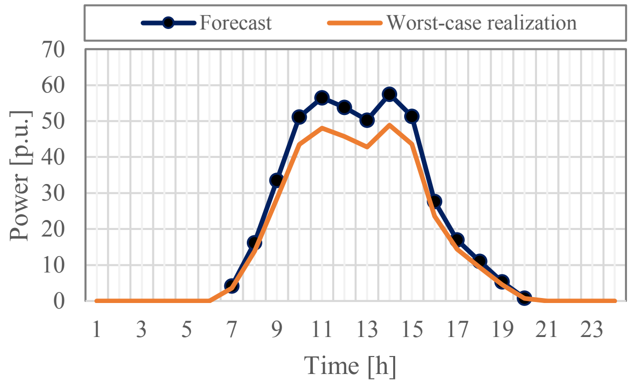

Fig. 4. Worst-case realization of PV generation

The outer loop is conducted due to the use of a C&C decomposition, while the inner loop is conducted for the BCD technique. The structure of this procedure, showing the interactions between the master and subproblems is shown in Fig. 2, where the inner loop path is shown using blue arrows and the outer loop path are indicated by the red arrows.

As no duality is conducted in the model, the binary decision variables indicating battery charging/discharging status as well as buying/selling bids can be obtained as "wait-and-see" variables under the worst-case realization of uncertainties obtained in the second-stage sub-problem. Therefore, the obtained RO solutions are recourse-based, meaning more practical and feasible solutions against uncertainties of PV generation and market prices.

IV. Simulation Results

A. Data Set

Simulations were performed for a 24-hour operating horizon using forecasted load data from [16]. The forecast PV generation has been considered for a north facing 600kW PV with 30° tilt using solar insolation and ambient temperature data for Port Augusta, South Australia. The steady state energy loss of the ESS was set at 2% of the system capacity. Base value for power is 10 kW in the perunit system. ESS capacity is considered as 500 kWh. A time-of-use electricity tariff is used with where both buying and selling prices are the same, at 41.53 ¢/kWh for hours 07-20 and 27.01 ¢/kWh at other times. There are 48 uncertain parameters because of the hourly uncertain price and uncertain PV generation in a 24 hour operating window. Simulations were conducted using BARON solver in GAMS software package [17].

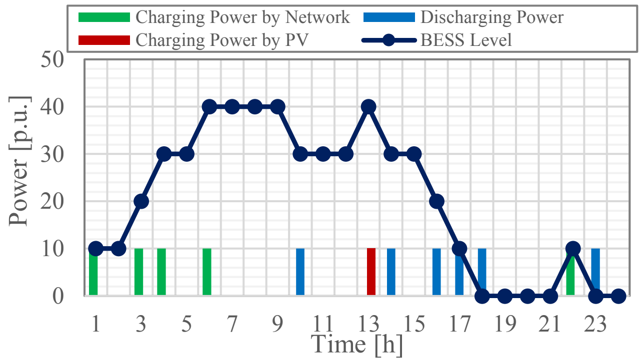

Fig. 5. Optimal operation (State-of-the-charge, charging/discharging power) of ESS

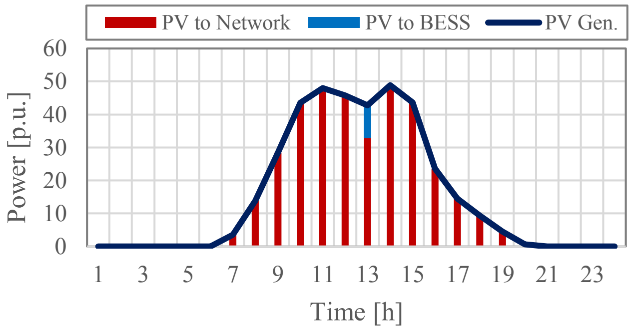

Fig. 6. Optimal PV interaction with ESS and network

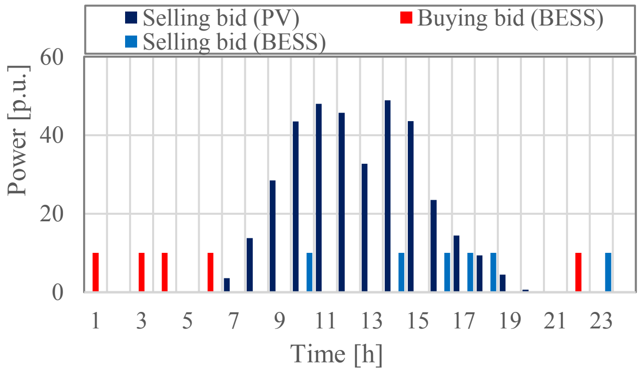

Fig. 7. Optimal bidding strategy of the PV-ESS plant in a 24-h operating horizon

BARON solver uses CPLEX to find the optimal solution in GAMS. The simulation has been conducted on a laptop computer with a core-i5 CPU and 8 GB RAM.

B. Results

Simulations have been conducted for two scenarios including the deterministic and the robust model. In fact, the value of Ψ is considered zero in the deterministic model, while it is considered as 48 in the RO model. Simulation results for the worst-case realization of uncertain parameters are as follows.

The worst-case realization of both market price and PV generation is shown by Fig. 3 and Fig. 4, respectively. As it is seen, the electricity price has increased in some hours at the start of the operating horizon.

It deserves mentioning that the worst-case realization of market price is not necessarily just descending or ascending. It may also stay unchanged if it appears as a worst-case realization in the inner max problem. This is due to the fact that the worst-case realization of market price can be ascending, if buying, or descending, if selling. Therefore, it can happen in both ways. The PV generation, however, has been reduced in all hours as it is obvious that any reduction in PV generation results in a worst-case for the plant operation (energy surplus never results in extra costs, while energy shortage does). Therefore, the worst-case realization of PV generation has reduced in all hours, compared to its forecast.

The optimal operation of an ESS under the worst-case realization of uncertain market price and PV generation is given by Fig. 5. As it is seen, the ESS can be charged by both the PV plant and the network. However, it has been mostly charged by the network throughout the day, except in hour 13 where it has charged by the PV plant. The optimal interaction of PV plant with an ESS and network is also given by Fig. 6. As it is seen, all the generated power by PV plant has been sold to the network, except in hour 13 in which the ESS has been charged by the PV power.

Finally, the optimal bidding strategy of the coupled PV-ESS plant has been given by Fig. 7. As it is seen, the PV plant has contributed in the majority of the selling bid, while the buying bids are all allocated to ESS charging power. The ESS has also been discharged in hours where no PV power is available, which shows the arbitrage ability of the ESS in providing more flexibility and market participation for the PV-ESS plant. The obtained RO solutions in Figures 3-7 are based on the considered worst-case realization of uncertainties throughout the operating horizon. Moreover, the use of the BCD technique provides the opportunity to characterize buying/selling bids as well as ESS charging/discharging status after uncertainty realizations as recourse actions.

V. CONCLUSION

This paper has presented a block coordinate decent robust optimization for developing a bid strategy for a coupled PV-ESS plant to maximise the benefit when operating in a day ahead market, while managing the uncertainty in future PV generation and market prices. The uncertainties were modelled by polyhedral uncertainty sets while the robust settings, including the uncertainty budget and the deviation range of uncertainties, were controlled by the operator. The BCD technique was employed instead of duality theory to solve the second-stage problem. This results in more practical/feasible solutions as the ESS charging/discharging status as well as the PV-ESS buying/selling status were obtained after the uncertainty realizations. The obtained solutions were reported on the worst-case realization of uncertain PV generation and market price. The optimal operation of the plant as well as its optimal bidding strategy was also determined and reported in the simulation results. The proposed model can assist PV-ESS merchants to participate in the market and gain extra benefits by taking advantage of the proposed BCD robust optimization model. Future work will be focused on conducting the BCD robust model on hybrid systems including electricity and gas networks.

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