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RESEARCH ARTICLE

# Optimal Look-Ahead Strategic Bidding/Offering of Integrated Renewable Power Plants and CAES With Stochastic-Robust Approach

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**ABSTRACT** Today, due to the high penetration of renewable energy resources and restructuring of power systems, photovoltaic power plants (PVPPs) and wind power plants (WPPs) as renewable power plants (RPPs) can participate in the electricity markets. However, the intermittent power generation of RPPs may be challenging for the owners of these power plants. In order to mitigate the unpredictable and intermittent power generation of RPPs, energy storage systems like compressed air energy storage (CAES) can be an appropriate solution. In this paper, the optimal day-ahead and look-ahead strategic offering and bidding of integrated RPPs and CAES in the electricity market are investigated. Also, a stochastic-robust approach is proposed for modeling renewable generation and electricity price uncertainty. The proposed mixed-integer linear program (MILP) is formulated in GAMS software under the CPLEX solver. Three case studies are investigated to validate the proposed method. According to numerical results, in the optimistic strategy, the coordinator of RPPs and CAES has more opportunities to participate in the electricity market. But in the pessimistic strategy, due to low electricity market (EM) prices, the coordinator has no more tendency to participate in the electricity market compared to the optimistic strategy.

**INDEX TERMS** Look-ahead, stochastic-robust approach, strategic bidding and offering, renewable power plants, CAES.

## NOMENCLATURE

### A. INDICES

| | Definition |
|---|---|
| $h$ | Index of time for $LA$. |
| $s$ | Index of scenarios. |
| $t$ | Index of time for $DA$. |

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### B. PARAMETERS

| | |
|---|---|
| $Price_t^{e,D0}$ | EM price for $D0$ at time $t$. |
| $Price_h^{e,D1}$ | EM price for $D1$ at time $h$. |
| $\rho_s$ | Probability of each scenario. |
| $P_t^{W,D0}$ | Produced power of WPP for $D0$ at time $t$. |
| $P_t^{PV,D0}$ | Produced power of PVPP for $D0$ at time $t$. |
| $\eta^{C,ch}$ | Charging efficiency of CAES. |
| $\eta^{C,dis}$ | Discharging efficiency of CAES. |

$V_{Min}^{C,ch}$ Minimum injected air to CAES in the charging mode.
$V_{Max}^{C,ch}$ Maximum injected air to CAES in the charging mode.
$V_{Min}^{C,dis}$ Minimum extracted air from CAES in the discharging mode.
$V_{Max}^{C,dis}$ Maximum extracted air from CAES in the discharging mode.

$A_{Initial}^{C}$ Initial LoA of CAES.
$A_{Min}^{C}$ Minimum LoA of CAES.
$A_{Max}^{C}$ Maximum LoA of CAES.
$\eta^{PV}$ Efficiency of PVPP.
$R_t^{PV,D0}$ Solar radiation in PVPP for $D0$ at time $t$.
$V_t^{Wind,D0}$ Wind speed in WPP for $D0$ at time $t$.
$V_{Ci}^{W}$ Cut-in speed of wind turbines in WPP.
$P_R^{W}$ Rated power of wind turbines in WPP.
$V_R^{W}$ Rated speed of wind turbines in WPP.
$V_{Co}^{W}$ Cut-out speed of wind turbines in WPP.
$P_{t,s}^{W,D1}$ Produced power of WPP for $D1$ at time $h$.
$P_{h,s}^{PV,D1}$ Produced power of PVPP for $D1$ at time $h$.
$R_{h,s}^{PV,D0}$ Solar radiation in PVPP for $D1$ at time $h$ in scenario $s$.
$V_{h,s}^{Wind,D1}$ Wind speed in WPP for $D1$ at time $t$ in scenario $s$.
$\xi^{D1}$ Discount factor.
$N^{WT}$ Number of wind turbines in WPP.

## C. VARIABLES

$Profit^{T}$ Total profit.
$Profit^{D0}$ Profit of $D0$.
$Profit^{D1}$ Profit of $D1$.
$P_t^{M,D0}$ Bidding/offering of integrated system in EM for $D0$ at time $t$.
$P_t^{C,ch,D0}$ Charging power of CAES for $D0$ at time $t$.
$P_t^{C,dis,D0}$ Discharging power of CAES for $D0$ at time $t$.
$V_t^{C,ch,D0}$ Injected air to CAES in the charging mode for $D0$ at time $t$.
$V_t^{C,dis,D0}$ Extracted air from CAES in the discharging mode for $D0$ at time $t$.
$B_t^{C,ch,D0}$ Binary variable of CAES in charging mode for $D0$ at time $t$.
$B_t^{C,dis,D0}$ Binary variable of CAES in charging mode for $D0$ at time $t$.
$A_t^{CAES,D0}$ LoA of CAES for $D0$ at time $t$.
$P_{h,s}^{M,D1}$ Bidding/offering of integrated system in EM for $D1$ at time $h$ in scenario $s$.
$P_{h,s}^{C,ch,D1}$ Charging power of CAES for $D1$ at time $h$ in scenario $s$.
$P_{h,s}^{C,dis,D1}$ Discharging power of CAES for $D1$ at time $h$ in scenario $s$.
$V_{h,s}^{C,ch,D1}$ Injected air to CAES in the charging mode for $D1$ at time $h$ in scenario $s$.
$V_{h,s}^{C,dis,D1}$ Extracted air from CAES in the discharging mode for $D1$ at time $h$ in scenario $s$.
$B_{h,s}^{C,ch,D1}$ binary variable of CAES in charging mode for $D1$ at time $h$ in scenario $s$.
$B_{h,s}^{C,dis,D1}$ binary variable of CAES in charging mode for $D1$ at time $h$ in scenario $s$.
$A_{h,s}^{CAES,D1}$ LoA of CAES for $D1$ at time $h$ in scenario $s$.

## D. ACRONYMS

CAES Compressed air energy storage.
EM Electricity market.
RPP Renewable power plant.
LA Look-ahead.
DA Day-ahead.
PVPP PV power plant.
WPP Wind power plant.

# I. INTRODUCTION

## A. MOTIVATION

Fossil fuels depletion and environmental issues have raised the penetration of renewable energies (especially solar and wind energies) in the electricity system for power production. One of the main problems related to renewable power plants (RPPs) is the uncertain output of these energy resources. Due to this feature, the participation of PV power plants (PVPPs) and wind power plants (WPPs) in the electricity market may face great challenges. To overcome this concern, storage devices can be used in pairs with RPPs to achieve higher profits in the electricity market. Storage device profitability can be increased by adjusting the final state of charge (SOC) on the first day in the look-ahead (LA) framework. However, optimal decisions of storage device paired RPPs in the electricity market are affected by electricity price uncertainty. Therefore, to achieve better results, uncertainties of renewable energies and electricity prices must be considered in the decisions of the integrated system.

## B. LITERATURE REVIEW

In the literature, there are various types of research that focus on the operation of renewable energies individually or integrated with storage devices in the electricity system. References [1], [2], [3], [4], [5], [6], [7], [8] have evaluated the individual participation of WPP in the electricity market. Reference [1] has described an offering strategy based on the minimization imbalance cost of WPP. In [2], the best offering strategy for a WPP that participates in the different floors of the electricity market has been presented, taking uncertainties of wind energy and electricity price into account. Authors of alashery2019second have introduced an offering model for the WPP based on second-order stochastic dominance constraints. An optimization model for the participation of thermal units and WPP in the medium and long-term electricity markets is presented in [4]. Reference [5] has provided a strategy in which WPP participates in the electricity market as a price-maker. The introduced strategy in [6] considers wind producers as a price-taker in the day-ahead (DA) market and as a price-maker in the balancing market. In [7], uncertain parameters have been handled through the information gap decision theory (IGDT) method. A bi-level model has been used in [8] to minimize the operation cost of grid-connected energy hubs, which include wind power.

Power production of WPP is usually high during midnight as well as in the winter season. On the other hand, PVPP can generate electricity during the daytime and their production decreases in winter. So, the characteristics of these two energies show that they complement each other. Given that solar and wind energies have complementary characteristics, some studies have analyzed the coordinated operation of these systems in the electricity network. Reference [9] has evaluated the coordinated operation of WPP and PVPP from the economic viewpoint. Authors in [10] have proposed a stochastic model for the trading of coordinated RPPs in the DA market. Reference [11] has offered a stochastic bi-objective framework for an integrated solar-wind-thermal system considering uncertainties of renewable energies and price. The aim of the first objective function is the profit maximization of the integrated system and the aim of the second one is emission minimization.

However, when renewable energies participate in the electricity market without storage devices, they have to buy/sell their shortage/surplus power at higher/lower prices from/to the market. Storage devices can increase total profits by shifting the power of renewable resources from low-priced moments to high-priced moments. Therefore, to achieve higher profits, storage devices can be integrated with renewable energies. There are various types of storage devices such as flywheels [12], batteries [13], pumped storages [14], and compressed air energy storages (CAES) [15]. Among these storage devices, only pumped storage and CAES have the capability to store a significant amount of energy [16]. However, the round-trip efficiency of CAES is usually higher than of pumped storage [17]. CAES consumes power to store compressed air in the underground reservoir or salt cavern, and it generates power using compressed air as an expander air for the turbine [18].

An operation strategy has been provided in [19] to earn higher profits for the CAES. Reference [20] has used a stochastic method for CAES participation in the energy market. In the same study, the downside risk constraint approach is applied to manage the risk of electricity price uncertainty. An IGDT-based self-scheduling model of a CAES unit has been presented in [21] considering price uncertainty. References [22] and [23] have evaluated participation of CAES in DA and ancillary service markets. Authors of [24] have proposed an optimal bidding/offering strategy for a CAES unit based on the stochastic-robust method. In that work, the uncertainty of storage capacity has been modeled through a robust approach, while a stochastic method has been used to model price uncertainty. It should be noted that no renewable energy in [19], [20], [21], [22], [23], and [24]. In reference [25], CAES has included in a network constrained unit commitment (UC) model to provide contingency reserves. Reference [26] has presented an IGDT-based UC model to evaluate the role of CAES in energy and reserve markets, considering the uncertainty of wind output. Scheduling of WPP and CAES has been studied in [27]. However, in this study, WPP and CAES are not coordinated and they operate separately. Participation of WPP paired with CAES and battery in DA and intraday markets has been evaluated through a stochastic framework in [28]. The work has also considered wind and electricity price uncertainties in the proposed model and used the conditional value at risk index to manage risk. Battery degradation cost is also included in that model. In [29], a similar study to [28] has been carried out and it has evaluated the optimal behavior of hybrid power plant containing CAES, WPP, and concentrating solar power plant in DA and intraday markets. These works have used the stochastic method to model uncertain parameters. Reference [30] has presented an offering strategy for the participation of coordinated CAES and the WPP in different electricity markets considering uncertain parameters. Moreover, the work has modeled the uncertainty of DA price via a robust approach while it has used the stochastic method to model uncertainties related to intra-day and balancing market prices as well as wind power. CAES and WPP participation in energy and ancillary service markets is modeled through the distributionally robust method in [31]. A risk-constrained strategy has been provided in reference [32] in which CAES and wind power aggregator have participated as a hybrid power plant in electricity markets (DA, intra-day, and balancing markets).

One important parameter that can increase the profitability of CAES is the SOC value at the end of the first day. Since this value is equal to the initial SOC on the second day, therefore, it affects the profitability of CAES on the second day. The LA framework has been vastly applied to adjust the SOC of storage devices. In this framework, DA refers to the first day, while LA refers to the second day. Reference [33] has applied the LA framework for scheduling an energy hub that contains energy storage systems. In this paper, uncertain parameters are modeled through the stochastic method. In [34], the LA bidding model has been presented for the integrated wind farm and concentrating PVPP equipped with thermal energy storage. Authors of [35] and [36] have used LA risk-constrained models in their research. Reference [35] has proposed a LA bi-level model in which the upper-level problem maximizes the profit of energy storage while the lower-level problem maximizes social welfare. In reference [36], the LA framework has been used to minimize the total cost of a system that includes wind and thermal units as well as CAES.

### C. NOVELTIES AND CONTRIBUTIONS

The following research gaps can be found in the reviewed studies:

- Some studies, for example [1], [2], [3], [4], [7], [10], [11], have evaluated the operation of renewable energies without CAES. Some others, e.g [19], [20], [21], [22], [23], [24], have evaluated the individual operation of the CAES in the electricity market. However, the individual participation of renewable energies and CAES in the electricity market is less profitable, and coordination of these technologies leads to higher profit for the integrated system.

- References [27], [28], [30], [31], [32] have studied the participation of integrated WPP and CAES units in the electricity market and they have not considered solar energy. However, wind power and solar energy have complementary characteristics and joint bidding of these energy resources is more profitable. Also, in this research, the trading horizon has been restricted to one day. However, by extending the trading horizon to two days through the LA framework, the optimal value for the final SOC of the CAES unit on the first day is determined and the total profit of the integrated system increases.
- References [34], [35], [36] have used the stochastic method to model uncertain parameters in their LA model. However, this approach is not a suitable choice for handling all uncertain parameters. As mentioned in [37], the robust method is a suitable choice for modeling electricity price uncertainty and the stochastic approach is suitable for modeling the uncertainty of renewable energies.

To address mentioned gaps, this paper proposes a bidding/offering strategy for the CAES system integrated with RPPs. This method maximizes the total profit of the integrated system for two consecutive days (the first day introduced as the DA and the second day introduced as the LA). In this paper, the uncertainties related to renewable energies and electricity prices on the second day are handled through a hybrid robust-stochastic approach. Uncertainty of renewable energies (wind and solar) are modeled through the stochastic method, while the robust approach is used to model the uncertainty of price. To the best of the authors' knowledge, it is the first work to use robust and stochastic methods to handle uncertainties in the bidding/offering model, taking the look-ahead framework into account. The major contributions of the paper can be declared as follows:

- Proposing a bidding/offering strategy for an integrated system that consists of a CAES system and RPPs with the aim of maximizing profit in two consecutive days.
- Considering a look-ahead framework in the proposed bidding/offering model. This framework proposes an opportunity to make a profit on the second day by determining the energy in the storage system at the end of the first day.
- Managing uncertainties of the second day through the hybrid robust-stochastic approach. This hybrid approach takes advantage of both uncertainty modeling methods.

### D. PAPER ORGANIZATION

The rest of the paper is organized as follows. The problem description and formulation of the proposed robust-stochastic model for optimal bidding/offering of integrated CAES system and RPPs are presented in sections II and III, respectively. Numerical results of simulations are provided in section IV. Finally, section V presents the conclusion of this paper.

## II. PROBLEM DESCRIPTION

The structure of the proposed model is shown in Fig.1. According to the proposed model, the coordinator is responsible for the optimal offering/ bidding of RPPs and CAES in the electricity market (EM). The coordinator has data trading with entities and is responsible for their optimal and secure operation. RPPs can sell either produced power to the electricity market or send it to CAES for the charging process. Also, the CAES system can purchase power from EM in the absence of RPPs or the low price of EM. With the high price of EM, CAES can offer energy to EM. The energy storage's state-of-charge (SoC) is one of the crucial parameters that have an important rule on the optimal operation of energy storage. Because the final SoC of energy storage on the first day can influence the scheduling of energy storage on the next day. So to do this, it is essential to calculate an optimal amount of initial (final) SoC for the next (first) day. Therefore in this paper, the optimization problem is investigated for two consecutive days (DA and LA). As mentioned above, CAES is utilized as an energy storage system in our proposed model. So instead of SoC, the level of air (LoA) of CAES is considered, which is in the same concept as SoC, and it shows the amount of stored air in the salt cavern. The optimization problem for DA is modeled deterministically. But for uncertainty assessment of renewable generation and electricity price, a hybrid stochastic-robust approach is taken into account for LA. The uncertainty related to renewable generation is handled by stochastic programming, and due to the tangible impact of electricity price on the optimal bidding/ offering of integrated RPPs and CAES in the EM, the robust optimization method is modeled for electricity price. The proposed model is not practically restricted and it can be used by owners of RPPs integrated with energy storage systems to better participate in the electricity market or it can be followed by the owner of smart homes and microgrids in order to improve the performance of these systems. Also, the proposed model is general and it can be developed for the different types of energy storage systems such as pumped hydro storage, battery storage, and hydrogen storage while being applied to large-scale or small-scale systems.

## III. PROBLEM FORMULATION

### A. STOCHASTIC-BASED MODEL OF INTEGRATED RPPs AND CAES SYSTEM

Initially, the mathematical problem is investigated without EM price uncertainty for simplicity, so only the uncertainty of RPPs generation is considered in the first step.

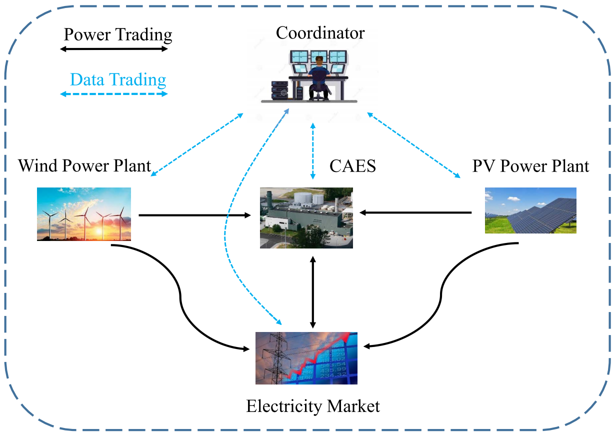


**FIGURE 1. Scheme of integrated RPPs and CAES.**

The mathematical formulation of the proposed model without considering the price uncertainty is represented in equations (1)-(25) and (26), as shown at the bottom of the next page. The objective function of the proposed mathematical model is defined as (1) that the goal is maximizing total profit. The first term of the objective function is the obtained profit for DA that can be calculated by (2), and the second one is related to obtained profit in the LA that is formulated by (3). These profits can be reachable by optimal bidding/ offering of the coordinator in EM. In equation (1), $\xi^{D1}$ is the discount factor which varies in the interval [0,1]. This factor indicates the intention of the integrated system coordinator to make a balance in profits of the first and second days. The different amount assigned to $\xi^{D1}$ affects the final LoA of CAES on the first day. The mathematical formulation of the DA problem is represented by (4)- (13) and (14), as shown at the bottom of the next page. The amount of bidden or offered power by the coordinator in EM can be expressed by (4) that the negative values of $P_t^{M,D0}$ represent the amount of purchased power by the coordinator from EM, and the positive values of $P_t^{M,D0}$ indicate sold power to EM. According to equation (4), the amount of purchased or sold power from/ to EM is dependent on the generation power of RPPs and the charging/ discharging power of CAES. Equations (5) and (6) show the linear relation between charging/ discharging power and charging/ discharging air of the CAES system. The permissible range of charging/ discharging air of CAES can be expressed by (7) and (8), respectively. Equation (9) avouches that the charging and discharging process of the CAES will not happen isochronal which binary variables $B_t^{C,ch,D0}$ and $B_t^{C,dis,D0}$ are used for this purpose. The amount of stored air at $t = 1$ and $t > 1$ can be calculated by (10) and (11), respectively. According to equations (10) and (11), the LoA at each time step $t$ belongs to stored air at previous time step $t-1$, amount of charging and discharging air. Equation (12) ensures that the LoA at any time step will be in an allowable range. Produced power of the PVPP can be calculated by (13), which has a relation to the efficiency of panels, solar radiation, and space of installed PV panels. Equation (14) expresses the amount of produced power by the wind turbines in WPP. It can be seen that the produced power has a non-linear affiliation with wind speed and as well as wind turbine characteristics.

$$Max\ \ Profit^T = Profit^{D0} + \xi^{D1} Profit^{D1} \tag{1}$$

$$Profit^{D0} = \sum_t^T Price_t^{e,D0} P_t^{M,D0} \tag{2}$$

$$Profit^{D1} = \sum_s^S \rho_s \sum_h^H Price_h^{e,D1} P_{h,s}^{M,D1} \tag{3}$$

$$P_t^{M,D0} = P_t^{W,D0} + P_t^{PV,D0} - P_t^{C,ch,D0} + P_t^{C,dis,D0} \quad \forall t \tag{4}$$

$$V_t^{C,ch,D0} = \eta^{C,ch} P_t^{C,ch,D0} \quad \forall t \tag{5}$$

$$P_t^{C,dis,D0} = \eta^{C,dis} V_t^{C,dis,D0} \quad \forall t \tag{6}$$

$$V_{Min}^{C,ch} B_t^{C,ch,D0} \leq V_t^{C,ch,D0} \leq V_{Max}^{C,ch} B_t^{C,ch,D0} \quad \forall t \tag{7}$$

$$V_{Min}^{C,dis} B_t^{C,dis,D0} \leq V_t^{C,dis,D0} \leq V_{Max}^{C,dis} B_t^{C,dis,D0} \quad \forall t \tag{8}$$

$$B_t^{CAES,ch,D0} + B_t^{C,dis,D0} \leq 1 \quad \forall t \tag{9}$$

$$A_t^{CAES,D0} = A_{Initial}^{C} + V_t^{C,ch,D0} - V_t^{C,dis,D0} \quad \forall t = 1 \tag{10}$$

$$A_t^{C,D0} = A_{t-1}^{C,D0} + V_t^{C,ch,D0} - V_t^{C,dis,D0} \quad \forall t > 1 \tag{11}$$

$$A_{Min}^{C} \leq A_t^{C,D0} \leq A_{Max}^{C} \quad \forall t \tag{12}$$

$$P_t^{PV,D0} = \eta^{PV} R_t^{PV,D0} S^{PV} \quad \forall t \tag{13}$$

The LA problem is expressed by (15)- (26). The constraints of the LA problem are similar to the DA problem, but some dissimilarities can be seen. a) Due to considering the uncertainty of RPPs generation, the set of scenarios $s$ is added to variables and parameters. b) Initial LoA in the LA (i.e. $h = 1$) will depend on the final LoA in the DA (i.e. $t = 1$) that this interrelation can be formulated by (21). c)According to (23), the final LoA at the end of the LA time horizon (i.e. $h = 24$), will be equal to the initial LoA in the DA.

$$P_{t,s}^{M,D1} = P_{t,s}^{W,D1} + P_{h,s}^{PV,D1} - P_{h,s}^{C,ch,D1} + P_{h,s}^{C,dis,D1} \quad \forall h, s \tag{15}$$

$$V_{h,s}^{C,ch,D1} = \eta^{C,ch} P_{h,s}^{C,ch,D1} \quad \forall h, s \tag{16}$$

$$P_{h,s}^{C,dis,D1} = \eta^{C,dis} V_{h,s}^{C,dis,D1} \quad \forall h, s \tag{17}$$

$$V_{Min}^{C,ch} B_{h,s}^{C,ch,D1} \leq V_{h,s}^{C,ch,D1} \leq V_{Max}^{C,ch} B_{h,s}^{C,ch,D1} \quad \forall h, s \tag{18}$$

$$V_{Min}^{C,dis} B_{h,s}^{C,dis,D1} \leq V_{h,s}^{C,dis,D1} \leq V_{Max}^{C,dis} B_{h,s}^{C,dis,D1} \quad \forall h, s \tag{19}$$

$$B_{h,s}^{C,ch,D1} + B_{h,s}^{C,dis,D1} \leq 1 \quad \forall h, s \tag{20}$$

$$A_{h,s}^{C,D1} = A_t^{C,D1} + V_{h,s}^{C,ch,D1} - V_{h,s}^{C,dis,D1} \quad \forall t = T, h = 1, s \tag{21}$$

$$A_{h,s}^{C,D1} = A_{h-1,s}^{C,D1} + V_{h,s}^{C,ch,D1} - V_{h,s}^{C,dis,D1} \quad \forall h > 1, s \tag{22}$$

$$A_{h,s}^{C,D1} = A_{Initial}^{C} \quad \forall h = H, s \tag{23}$$
$$A_{Min}^{C} \leq A_{h,s}^{C,D1} \leq A_{Max}^{C} \quad \forall h, s \tag{24}$$
$$P_{h,s}^{PV,D1} = \eta^{PV} R_{h,s}^{PV,D1} S^{PV} \quad \forall h, s \tag{25}$$

### B. SCENARIO GENERATION AND REDUCTION METHOD

In this paper, the stochastic method is used to handle uncertainties associated with wind and solar energies. Solar radiation and wind speed are uncertain parameters of these renewable energies, which depend on weather conditions. In the stochastic method, uncertain parameters are modeled considering their different realizations via proper scenario generation. Generally, beta and Weibull probability density functions (PDF) are used to generate scenarios pertaining to solar radiation and wind speed, respectively [38]. Equation (27) represents beta PDF in which $R$ is solar irradiance. $\alpha$ and $\beta$ are parameters of beta function that can be calculated by (28). As mentioned, wind uncertainty is modeled by Weibull PDF (29). In (30), $k$ and $c$ are shape and scale indices, respectively.

$$PDF(R) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times R^{\alpha-1} \times (1-R)^{\beta-1} \tag{27}$$
$$\beta = (1-\mu) \times \left(\frac{\mu \times (1-\mu)}{\delta^2} - 1\right), \quad \alpha = \frac{\mu \times \beta}{1-\mu} \tag{28}$$
$$PDF(V) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} exp\left(-\left(\frac{V}{c}\right)^{k}\right) \tag{29}$$
$$k = \left(\frac{\delta}{\mu}\right)^{-1.086}, \quad c = \frac{c}{\Gamma(1+\frac{1}{k})} \tag{30}$$

The computational burden of the stochastic method is highly dependent on the number of generated scenarios. So, to overcome this problem, applying scenario reduction techniques is necessary. In this work, the fast backward method of SCENRED tool of GAMS software is used to reduce 1000 generated scenarios to 10.

### C. ROBUST OPTIMIZATION APPROACH

The general form of an optimization problem is presented in (31)-(34).

$$\underset{x_h,\forall h}{Min} \sum_{h}^{H} \varphi_h x_h \tag{31}$$
$$\text{S.t.} \sum_{h}^{H} A_{jh} x_h \leq B_j \quad \forall j \tag{32}$$
$$x_h \leq 0 \quad \forall h \tag{33}$$
$$x_h \in \{0, 1\} \quad \forall h \tag{34}$$

In equation (31), $\varphi_h$ is an uncertain parameter that varies from $\varphi_h^{min}$ to $\varphi_h^{max}$. Therefore, the optimization problem (31)-(34) can be reformulated as a robust model.

$$\underset{x_t,\forall t}{Min} \sum_{h}^{H} \varphi_H x_h + \underset{\{h,h\leq\Pi\}}{Max} \left\{ \sum_{h} (\varphi_h^{max} - \varphi_h^{min})|x_h| \right\} \tag{35}$$
$$\text{S.t. } Equations (32) - (34) \tag{36}$$

In a robust model, the conservativeness level is controlled through an integer parameter that is called the budget of uncertainty ($\Pi$). The value assigned to this parameter is in $[0, H]$. If $\Pi = H$, it means that the decision-maker makes the most conservative decisions and considers uncertainty in all periods. If $\Pi = 0$, it means that the decision-maker ignores uncertainty. The robust counterpart of optimization models of (35) and (36) is given in (37)-(42) which is obtained through duality theory [39].

$$Min \sum_{h}^{H} \varphi_h x_h + z\Pi + \sum_{h}^{H} q_h \tag{37}$$
$$\text{S.t. } Equations\ (32) - (34) \tag{38}$$
$$z + q_h \geq (\varphi_h^{max} - \varphi_h^{min}) \times \lambda_h \quad \forall h \tag{39}$$
$$\lambda_h \geq 0 \quad \forall h \tag{40}$$
$$z \geq 0 \tag{41}$$
$$x_h \leq \lambda_h \quad \forall h \tag{42}$$

$\lambda$, $q$ and $z$ are dual variable of constraints.

$$P_t^{W,D0} = N^{WT} \times \begin{cases} 0 & V_t^{Wind,D0} < V_{Ci}^W & \forall t \\ P_R^W \left(\dfrac{V_t^{Wind,D0} - V_{Ci}^W}{V_R^W - V_{Ci}^W}\right)^3 & V_{Ci}^W \leq V_t^{Wind,D0} < V_R^W & \forall t \\ P_R^W & V_R^W \leq V_t^{Wind,D0} < V_{Co}^W & \forall t \\ 0 & V_t^{Wind,D0} \geq V_{Co}^W & \forall t \end{cases} \tag{14}$$

$$P_{h,s}^{W,D1} = N^{WT} \times \begin{cases} 0 & V_{h,s}^{Wind,D1} < V_{Ci}^W & \forall h,s \\ P_R^W \left(\dfrac{V_{h,s}^{Wind,D1} - V_{Ci}^W}{V_R^W - V_{Ci}^W}\right)^3 & V_{Ci}^W \leq V_{h,s}^{Wind,D1} < V_R^W & \forall h,s \\ P_R^W & V_R^W \leq V_{h,s}^{Wind,D1} < V_{Co}^W & \forall h,s \\ 0 & V_{h,s}^{Wind,D1} \geq V_{Co}^W & \forall h,s \end{cases} \tag{26}$$

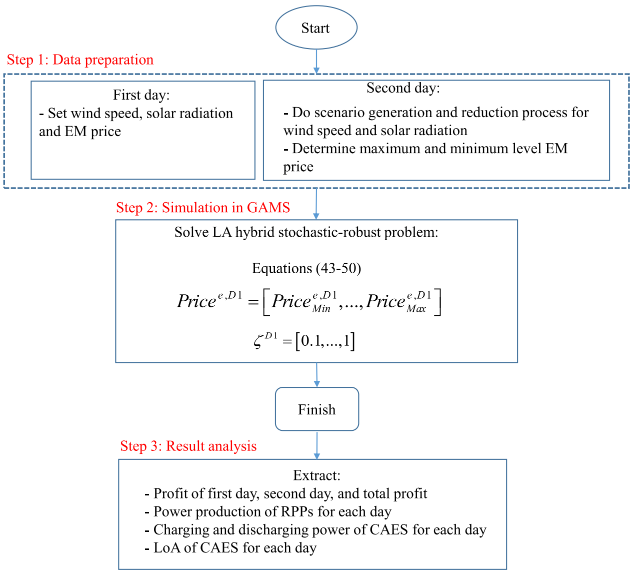


**FIGURE 2.** Flowchart of the proposed model.

### D. STOCHASTIC-ROBUST BASED MODEL OF INTEGRATED RPPs AND CAES SYSTEM

The general mathematical model of robust optimization approach introduced by (37)-(42). According to the proposed model in [30], the minimization problem of a robust optimization can convert to a maximization problem. So for modeling price uncertainty using the robust optimization approach, the proposed stochastic based model in (1)-(26) can be reformulate by (43)-(50) to a stochastic-robust based model. The flowchart of the proposed model can be seen in Fig.III-C.

$$Max \;\; Profit^{T} = Profit^{D0} + \xi^{D1} Profit^{D1} \tag{43}$$

$$Profit^{D0} = \sum_{t}^{T} Price_t^{e,D0} P_t^{M,D0} \tag{44}$$

$$Profit^{D1} = \sum_{s}^{S} \rho_s \sum_{h}^{H} Price_h^{e,D1} P_{h,s}^{M,D1} - z\Pi - \sum_{h}^{H} q_h \tag{45}$$

$$\text{S.t. } Equations \; (4) - (26) \tag{46}$$

$$z + q_h \geq (Price_h^{e,D1,max} - Price_h^{e,D1,min}) \times \lambda_h \quad h = 1, \ldots, H \tag{47}$$

$$\lambda_h \geq 0 \quad h = 1, \ldots, H \tag{48}$$

$$z \geq 0 \tag{49}$$

$$P_{h,s}^{M,D1} \leq \lambda_h \quad h = 1, \ldots, H \tag{50}$$

## IV. SIMULATION AND NUMERICAL RESULTS

In the following section, problem inputs are introduced in the first subsection and numerical results are discussed in the second one. The proposed mixed-integer linear program (MILP) is implemented in the GAMS software under the CPLEX solver on an Intel Core i7, 12 GB RAM, and 2.7 GHz CPU.

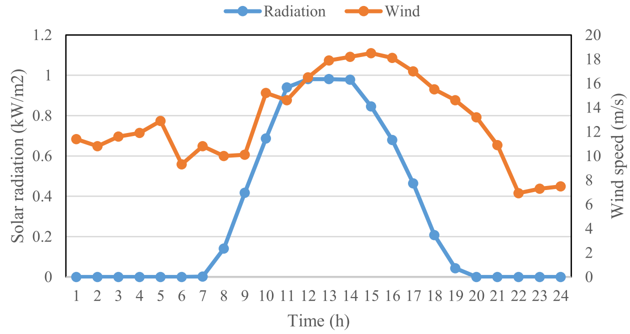


**FIGURE 3.** Solar radiation and wind speed.

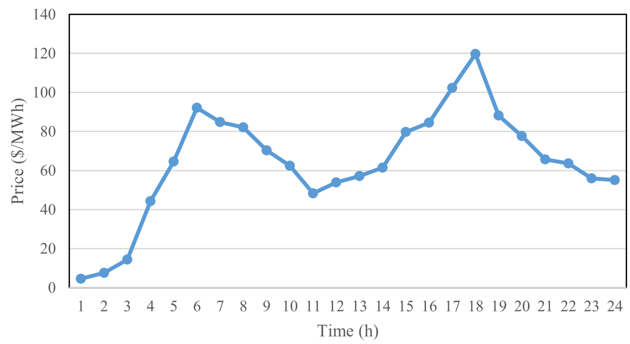


**FIGURE 4.** Day-ahead EM price.

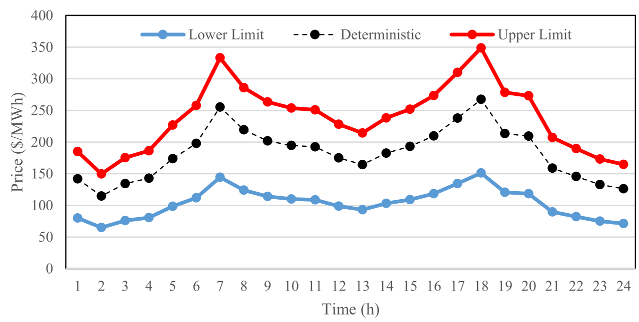


**FIGURE 5.** Look-ahead EM price.

**TABLE 1.** Probability of scenarios.

| Scenario | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Probability (-) | 0.17 | 0.06 | 0.02 | 0.09 | 0.12 |
| Scenario | 6 | 7 | 8 | 9 | 10 |
| Probability (-) | 0.14 | 0.07 | 0.20 | 0.08 | 0.05 |

### A. INPUT DATA

The DA solar radiation and wind speed are illustrated in Fig.3 [27], [40]. The EM price for DA is represented in Fig.4, but for uncertainty modeling of EM price for look-ahead, a permissible range of price is taken into account according to Fig.5 [33]. The LA solar radiation and wind speed for reduced scenarios are depicted in Fig.6 and Fig.7, respectively. Also, the probability of reduced scenarios is presented in Table 1. The technical data of RPPs is provided in Table 2. Furthermore, usable information for the simulation CAES system is prepared in Table 3.

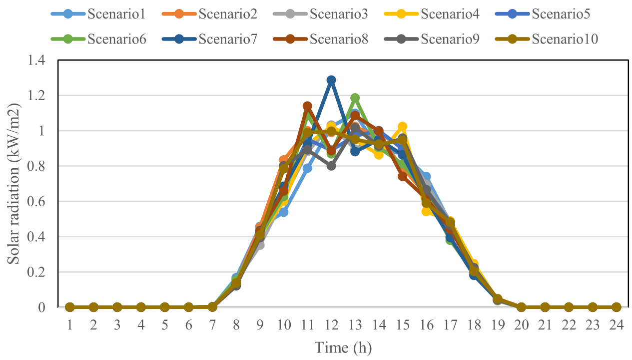


**FIGURE 6.** LA solar radiation for various scenarios.

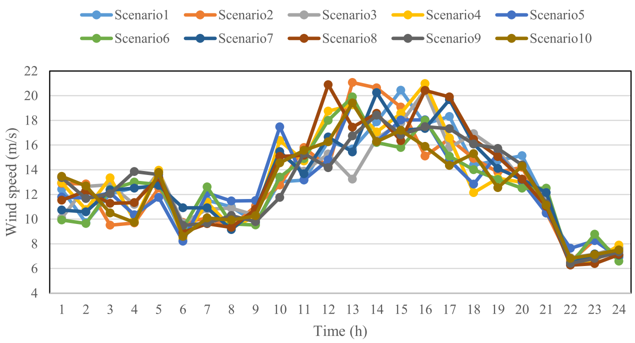


**FIGURE 7.** LA wind speed for various scenarios.

**TABLE 2.** Technical data of PV and wind power plants.

| | | | | |
|---|---|---|---|---|
| *PV power plant* | | | | |
| $\eta^{PV}$ $(-)$ | $S^{PV}$ $(m^2)$ | | | |
| 0.95 | 10000 | | | |
| *Wind power plant* | | | | |
| $V_{Ci}^{W}$ $(m/s)$ | $V_{Co}^{W}$ $(m/s)$ | $V_{R}^{W}$ $(m/s)$ | $P_{R}^{W}$ $(MW)$ | $N^{WT}$ $(-)$ |
| 2 | 25 | 14 | 2 | 20 |

### B. SIMULATION RESULTS

In this paper, three different case studies are investigated for validating the efficacy of the proposed model. In the first case, the RPPs participate in day-ahead EM without integration of CAES. In the second one, the integrated CAES and RPPs participate in day-ahead EM. The third case study is categorized into two frameworks (FWs). In the first one, the optimal strategic bidding/ offering of the integrated CAES and RPPs in the EM without considering of interconnection of DA and LA is investigated, and in the second FW, the influence of DA and LA interconnection through stored air of CAES is perused on the bidding/ offering of the proposed model. Also, the uncertainty assessment of RPPs generation and EM price is just studied in the third case study.

#### 1) CASE 1

In this case, the RPPs offer produced power in day-ahead EM without integration of CAES. The obtained profit for this case is \$ 51954.730. Fig.8 indicates the optimal offering of RPPs in the DA market. In this figure, the aggregated bar represents the total produced power by RPPs, and the black line shows the amount of power offered to EM. According to Fig.8, it can be seen that the produced power of RPPs is not in harmony with EM price. It means that the produced power of RPPs in the high EM prices, i.e., the hours 6:00, 7:00, 17:00, and 18:00, is relatively low, and they can not offer more power at the high EM price, so it results in less profit. That is because of the non-dispatchable behavior of RPPs. To overcome the techno-economic challenge of RPPs, energy storage systems can integrate with them. In the next case study, the influence of integrated CAES with RPPs will be discussed in more detail.

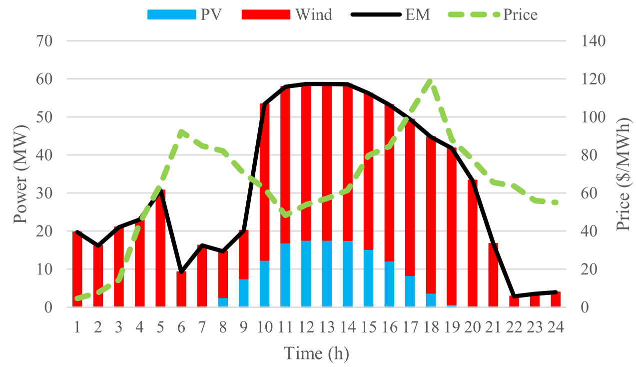


**FIGURE 8.** Offering of RPPs in the DA market for case 1.

#### 2) CASE 2

The optimal strategic bidding/ offering of integrated CAES and RPPs in the DA market is studied in this case. The optimal operational strategy of the integrated system is shown in Fig.9, and the obtained profit for this case is \$ 63499.57. Compared to the first case study, due to the strategic behavior of CAES, the profit increment is noticeable. As mentioned earlier, the coordinator receives the signals from entities and is responsible for their optimal and secure operation. So to do this, the coordinator sends signals to charging CAES during low EM prices and discharging it during high EM prices. As a result, this strategic behavior results in more power offerings in the DA market, so it will be more beneficial. The stored air of CAES is depicted in Fig.10. It can be seen that the LoA air at the end of the time horizon is equal to the initial amount. This predetermined amount of stored air at the end of the time horizon may not be economical for the second day's optimal operation, so it is needful to calculate an optimal amount of stored air for the end of the first day. To cover this argument, the optimal bidding/ offering of the proposed model for the DA and LA problem is investigated in the third case study.

#### 3) CASE 3

The optimal strategic bidding/ offering of integrated CAES and RPPs in the DA and LA market, considering uncertainties of RPPs generation and EM price, is studied in this case. In the first step, the uncertainty of EM price is not considered and only the RPPs generation's uncertainty is taken into account. The uncertainty assessment of EM price will be discussed in the second step. As mentioned, two FWs are taken into account for this case study. In the first FW, there is no interconnection between the DA and LA problems.

**TABLE 3. Technical data of CAES system.**

| CAES | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $\eta^{C,ch}$ $(-)$ | $\eta^{C,dis}$ $(-)$ | $V^{C,ch}_{Min}$ $(Mm^3/h)$ | $V^{C,ch}_{Max}$ $(Mm^3)$ | $V^{C,dis}_{Min}$ $(Mm^3)$ | $V^{C,dis}_{Max}$ $(Mm^3)$ | $A^{C}_{Min}$ $(Mm^3h)$ | $A^{C}_{Max}$ $(Mm^3h)$ | $A_{Initial}$ $(Mm^3h)$ |
| 0.95 | 0.95 | 5 | 30 | 5 | 30 | 40 | 180 | 80 |

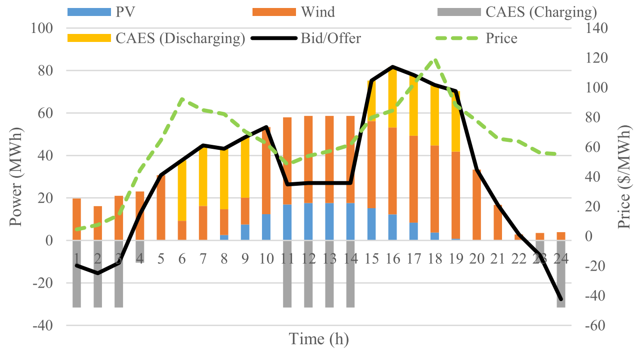


**FIGURE 9. Optimal bidding/offering of integrated RPPs and CAES in the DA market for case 2.**

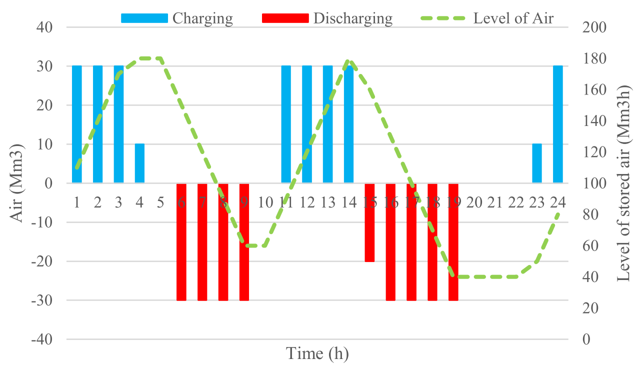


**FIGURE 10. Air level of CAES for case 2.**

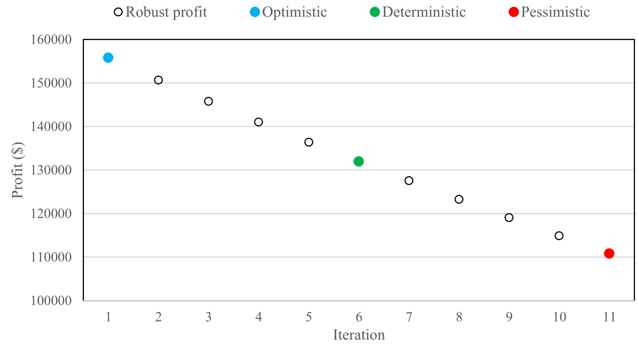


**FIGURE 11. Robust profit of the proposed model.**

In other words, the final LoA of each day must be equal to the initial amount of it. But in the second FW, the interconnection between the DA and LA problems is taken into account, so the LoA will be an optimal value. The LoA at the end of DA and obtained profits of DA and LA are analyzed for various amounts of $\xi^{D1}$ in Table4. For the first FW, the amount of stored air at the end of the first day ($A^{C,D0}_{t=24}$) and profit of the first day ($Profit^{D1}$) is constant, and it is because of independent scheduling of DA and LA problem. But for the second day, it can be seen that by increasing of $\xi^{D1}$ the obtained profit for the second day scaled up. So the amount of total profit will be increased. This is because the scheduling of two consecutive days increases the total profit, and this is what we already expected. For FW 2, due to the dependency of DA and LA problems on each other, for various amounts of $\xi^{D1}$, $Profit^{D0}$ and $A^{C,D0}_{t=24}$ are changing. For $\xi^{D1} = 0.3$ the total profit for FW 2 is obtained \$ 83995.2, and compared to FW 1, the total profit has increased by \$ 1381.7. In this state the optimal amount of $A^{C,D0}_{t=24}$ is calculated 40 $Mm^3h$. It shows that if the scheduling of the LA problem is nonsignificant, there is no need to select a large amount of LoA at the end of the time horizon. On the contrary, if the scheduling of the LA problem is significant, the large amounts of final stored air will be beneficial. For example, for $\xi^{D1} = 1$ the total profit is increased by \$127.7 compared to FW 1. Also, the optimal amount of stored air is calculated 100 $Mm^3h$ for $\xi^{D1} = 1$.

In the second step, simulation results will be discussed under EM price and RPPs generation uncertainty. The robust profit for the proposed bidding/offering model of the DA and LA problem is proposed in Fig.11 for FW 2. According to Fig.11, the optimistic, deterministic and pessimistic profit is obtained \$155772.7, \$131946.3 and \$110794.1 respectively. In the optimistic strategy, the integrated system has more opportunities to get more profit because of the high EM price. But in the pessimistic strategy that indicates the worst-case of EM price uncertainty, the integrated system does not have more tendency to participate in EM. So it results in less profit compared to the deterministic and pessimistic strategy.

The optimal bidding/offering of the integrated system for DA under FW 2 is presented in Fig.12. As can be observed in the optimistic strategy, the amount of power bought by the system is increased. It is because the EM price of LA is supposed to be higher than the expected values, so the coordinator of the system decides to charge the CAES with large amounts at 21:00- 24:00, which leads to bidding more power in the DA and offering more power on the second day with high EM price. In contrast, for EM prices lower than the expected values (worst-case), the charging power of CAES at 21:00- 24:00 is decreased. It shows that the system coordinator will not offer more power in the LA market. The final LoA of CAES for DA under various amounts of $\xi^{D1}$ is presented in Fig.13. It is clear that with increasing of $\xi^{D1}$ the amount of stored air is scaling up, which for the optimistic strategy is higher than the deterministic and pessimistic strategy. It shows that for the high EM price of LA, the amount of final stored air will be increased.

Optimal bidding curves for $h = 2$ and $\xi^{D1} = 1$ is demonstrated in Fig.14 for three different scenarios. As shown for the first and seventh scenarios, the amount of bought power by the integrated system increased with high values of EM price. However, in these scenarios buying more power at the

**TABLE 4.** Simulation results for case study 3.

| | $\xi^{D1}$ $(-)$ | 0.3 | 0.6 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|
| FW1 | $A_{t=24}^{C,D0}$ $(Mm^3h)$ | 80 | 80 | 80 | 80 | 80 |
| | $Profit^{D0}$ ($) | 63499.5 | 63499.5 | 63499.5 | 63499.5 | 63499.5 |
| | $Profit^{D1}$ ($) | 20495.7 | 40991.4 | 54655.2 | 61487.1 | 68319 |
| | $Profit^{T}$ ($) | 83995.2 | 104491 | 118154.8 | 124986.7 | 131818.6 |
| FW2 | $A_{t=24}^{C,D0}$ $(Mm^3h)$ | 40 | 40 | 73 | 81 | 100 |
| | $Profit^{D0}$ ($) | 65828.6 | 65828.6 | 63557.7 | 63205.6 | 62320.8 |
| | $Profit^{D1}$ ($) | 20816.4 | 41632.9 | 58162.3 | 66646.7 | 75069.1 |
| | $Profit^{T}$ ($) | 85376.9 | 104925.2 | 118163.9 | 124992.8 | 131946.3 |

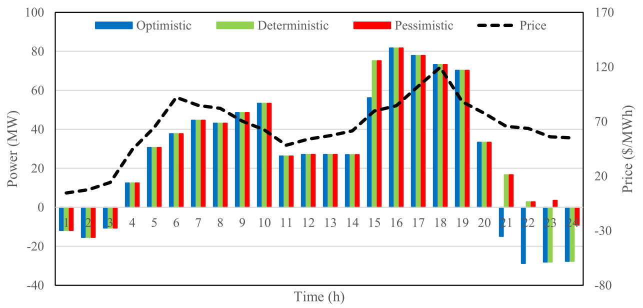


**FIGURE 12.** Optimal bidding/offering of the integrated system for DA under FW 2 in the case study 3.

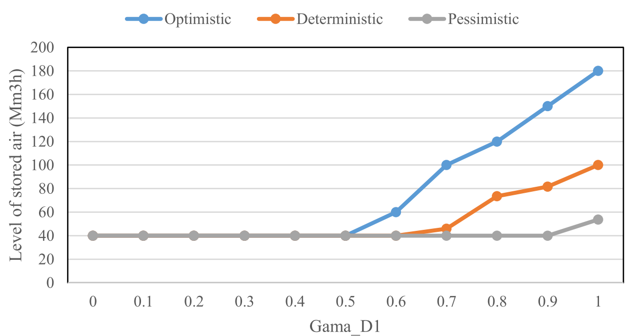


**FIGURE 13.** Final stored air of CAES for DA.

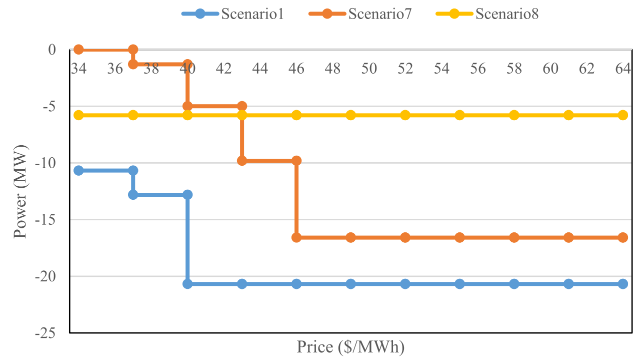


**FIGURE 14.** Optimal bidding curves for $h = 2$ and $\xi^{D1} = 1$.

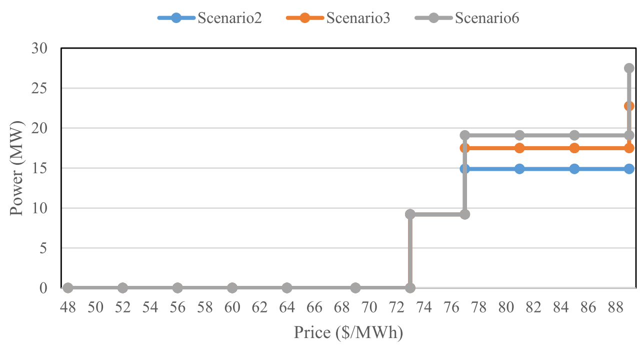


**FIGURE 15.** Optimal offering curves for $h = 21$ and $\xi^{D1} = 1$.

high EM price will cause selling more power at other times with the high EM price, so it can be beneficial. But for the eighth scenario, the amount of bought power is constant for different values of EM price, and due to the high penetration of RPPs, there is no need to buy more power. Also, the optimal offering curves for $h = 21$ and $\xi^{D1} = 1$ are represented in Fig.15 for scenarios 2, 3, and 6. As demonstrated in this figure, the amount of offering power is enlarged with the high EM price.

#### 4) CASE STUDIES DISCUSSION

In the first case study, the integration of CAES into RPPs was not considered. According to obtained results in this case study, the power production of RPPs is not coordinated with EM price, so it was not cost-effective from the RPPs owner's perspective. To overcome this challenge, in the second case study the integration of CAES into RPPs was investigated. Numerical results show that during low EM prices, CAES is charged by buying power from grid or RPPs production, and during high EM prices, it is discharged. This strategy increases the obtained profit and it is economical for the owner of RPPs. On the other side, the efficacy of the LA strategy was investigated in the third case study. it is seen that the proposed LA strategy in FW 2 increases the obtained profit. Therefore, this strategy can be suggested to the owner of RPPs integrated with CAES in order to obtain more profit.

## V. CONCLUSION

In this work, an optimal bidding/offering strategy is suggested for the participation of integrated RPPs with the CAES unit in EM. The hybrid robust-stochastic method is used to manage uncertainties in this model. It should be noted that uncertainty of EM price is handled by using the robust method while uncertainties of renewable energies are modeled via a stochastic approach. As well, in order to obtain higher profit in the proposed model, the LA technique is employed for adjusting the final LoA of the CAES unit. The effectiveness of the proposed bidding/offering strategy is evaluated in three cases. According to the obtained results from the first and second case studies, RPPs can make economic decisions when integrated with the CAES unit. They can sell their power directly to EM or store it in the storage device to achieve more profit. In case 3, the LA technique and uncertainties are considered in the proposed bidding/offering model. The results indicate that the LA technique can help to increase the total profit of the integrated system by setting the optimal value for the final LoA of the CAES unit. Moreover, in the optimistic strategy, the integrated system gets more profit compared to deterministic and pessimistic strategies. The reason for this is that when EM price is higher than its expected values, the coordinator of the integrated system has a greater desire to participate in EM. For future works, the optimal look-ahead bidding/offering of integrated renewable power plants and CAES in the electricity market considering the technical constraints of the power network with the presence of other participants in the wholesale electricity market can be investigated. Also, the uncertainties of the problem can be modeled by other methods such as IGDT and chance constraint.

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