Risk-Aware Bilevel Optimal Offering Strategy of a Joint Wind/Storage Unit Based on Information Gap Decision Theory

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***Abstract*—This article presents a robust approach for the optimal offering of joint wind/storage units in day-ahead nodal energy markets. The problem is formulated as a bilevel optimization problem wherein the upper level, the joint unit profit is maximized and at the lower level, the market is cleared by the system operator. The bilevel optimization problem is effectively formulated as a mathematical program with equilibrium constraints and converted to a trackable mixed-integer linear program. Information gap decision theory (IGDT) is implemented to manage the uncertainties caused by wind generation and price uncertainty of the system. Two different strategies are considered for optimal offering by IGDT including risk-averse and opportunity seeker strategies. While in the risk-averse approach conservative offers are submitted to assure a minimum profit, in the opportunity seeker strategy there is an optimistic view to uncertainties which can be exploited to increase the gained profit.**

***Index Terms*—Bilevel optimization, information gap decision theory (IGDT), joint wind/storage unit, mathematical program with equilibrium constraints (MPEC), optimal offering strategy.**

NOMENCLATURE

A. Sets and Indices

G	Set of generator buses.
W	Set of wind unit buses.
D	Set of load buses.
S	Set of storage unit buses.
N	Set of all buses.
L	Set of lines.
T	Set of hours.
t	Index for hour.
dis	Index for storage discharge.
ch	Index for storage charge.
i	Subscript for bus.
j	Subscript for bus.

B. Parameters

x	Generation unit price offers.
b	Demand price offers.
c	Wind unit price offers.
γ^{dis}	Discharge price offer for storage unit.
γ^{ch}	Charge price offer for storage unit.
$\gamma^{W,j}$	Wind generation price offer of the joint unit.
$P_i^{G,\min}$	Minimum generation of the unit at bus i.
$P_i^{G,\max}$	Maximum generation of the unit at bus i.
$P_i^{D,\min}$	Minimum demand of unit at bus i.
$P_i^{D,\max}$	Maximum demand of unit at bus i.
$P_i^{W,\max}$	Maximum generation of wind unit at bus i.
$P_i^{Wj,\max}$	Maximum generation of wind generation of the joint unit at bus i.
$P_{i,\mathrm{dis}}^{S,\min}$	Minimum discharge power of storage unit at bus i.
$P_{i,\mathrm{dis}}^{S,\max}$	Maximum discharge power of storage unit at bus i.
$P_{i,ch}^{S,\min}$	Minimum charge power of storage unit at bus i.
$P_{i,ch}^{S,\max}$	Maximum charge power of storage unit at bus i.
$E_{\min}$	Minimum stored energy.
$E_{\max}$	Maximum stored energy.
C_{ij}	Maximum line flow for the line between bus i and bus j.

C. Variables

P_i^G	Generation of the unit at bus i.
P_i^D	Demand of unit at bus i.
P_i^W	Wind generation at bus i.
P_i^{Wj}	Wind generation of the joint unit at bus i.
$P_{i,\mathrm{dis}}^S$	Storage joint unit discharge power at bus i.
$P_{i,ch}^S$	Storage joint unit charge power at bus i.
s_{dis}	Storage joint unit discharge state.
s_{ch}	Storage joint unit charge state.
E	Storage joint state of charge.
δ_i	Angle at bus i.
$PP_{\mathrm{dis}}^{\max}(t)$	Positive auxiliary variable.
$PP_{\mathrm{dis}}^{\min}(t)$	Positive auxiliary variable.
$PP_{\mathrm{ch}}^{\max}(t)$	Positive auxiliary variable.
$PP_{\mathrm{ch}}^{\max}(t)$	Positive auxiliary variable.
λ_i	Locational marginal price.

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I. Introduction

AFTER the liberalization of electricity markets in several countries since 1990, high consuming loads have purchased energy through bilateral contracts [1]. Other generation companies and distribution companies can handle their electricity trading in two different market designs including the pool model and exchange model. For the pool model, the electricity trading market is cleared through a pool where the generation and demand sides submit their offers and optimized decisions are applied. This model imitates the conventional vertical integrated system. This market is cleared for day ahead [1]. In addition to day-ahead markets, intraday markets all also practiced in several grids where the participants find the chance to modify their offers and the initial schedule [2]. Finally, for the energy, there is a real-time market where the generation dispatches and the price of energy are determined for the operating day. In addition to energy markets, ancillary service markets are designed to support the reliable transmission of energy between the producers and the consumers [3]. Many types of research have been conducted on clearing day-ahead energy markets considering wind [4] and energy storage units [5].

In the past decade, there has been a salient growth of installing and providing power by renewable energy, particularly wind energy [6]. Also, policies are regulated to encourage investments in wind farms and facilitate wind generation contribution in power markets [7]. However, due to the uncertainty of generation by wind power producers, they cannot participate in power markets similar to conventional units. Therefore, to take part in electricity markets, three different approaches, including participating in short-term markets, joint operation with flexible sources, and wind prediction with lower errors, are proposed [8]. Energy storage systems are among controllable devices that can be exploited to mitigate wind generation volatility and interruption. Although several wind farms and energy storage systems are subsidized and funded partially or totally by governments, appropriate strategies have to be developed for private owners to compete in power markets to maximize their benefit [9]. The joint operation of a wind farm and a storage system has been studied in [10] for three different markets consisting of day-ahead, intraday, and real-time markets. In this article, penalties are considered for drifting from the prescheduled generation. In [11], a stochastic programming approach is presented for the optimal offering of large-scale storage systems in energy and reserve markets. In [12], a framework for managing imbalances of wind farms utilizing storage systems with the goal of profit maximization is provided. In [13], the benefits of price-quantity bidding instead of quantity only bidding are shown.

In all of the above-mentioned references, the optimal offering problem is considered as a single-stage optimization problem without considering the actions of other participants and the market-clearing procedure. In [9], a linearized model for the optimal offering of large-scale geographically dispersed storage systems is presented. In [14], the annual arbitrage of a storage system is studied in a bilevel optimization model. An equilibrium problem with equilibrium constraints (EPEC) is introduced in [15] for the participation of multiple storage systems in a day-ahead market. In [16], the authors show that profit maximization of a storage unit can be contradictory with social welfare since the storage system tries to resume price volatility. Also, the market equilibrium for generation units, wind, and storage systems is studied in [17].

Few works of literature consider the uncertainties of various parameters for the bilevel optimal offering of joint wind/storage systems. In [18], a stochastic bilevel optimal offering approach is proposed for the participation of a storage system in energy and reserve markets which considers the net load uncertainty. Also, a stochastic programming approach is applied in [19] to handle the uncertainties of a virtual power plant. However, in this article, the line flow constraints are not considered. Besides, to utilize stochastic programming, statistical information must be available to generate the scenarios. Also, by increasing the number of scenarios to obtain a more accurate solution, the computational burden increases. Robust optimization has been used in [20] and [21] for the optimal bidding of virtual power plants and in [22], for the optimal offering of a compressed air energy storage system. Nevertheless, the formulation provided is a single-level optimization model that does not consider the lower level problem of clearing the energy market. A hybrid stochastic/IGDT formulation is proposed in [23] for an energy hub in a day-ahead market. Nonetheless, this article also does not consider the lower level and deals with the problem as a single-level optimization problem.

To reliably preserve a system's robust performance confronting with associated severe uncertainty margins while the required data are missing or not informative, information gap decision theory (IGDT) can be proposed as a simple, nonprobabilistic, and exact risk-hedging decision-making portfolio. The cornerstone of the IGDT uncertainty handling paradigm is to effectively model the discrepancy between what is known and what is expected to be known. In other words, procuring tractable robust solutions with reasonable computational efforts without dependency on the uncertainty distribution or membership functions leads the IGDT to be an attractive risk-aware methodology that could be utilized by system operators [24], [25]. Accordingly, the movement of the research toward applying the IGDT as a robust optimizer to the power system studies is uplifting. For example, the proficiency of the IGDT has been appraised in the microgrid bidding strategy [26], power system voltage control [27], hierarchical frequency management in smart grids [28], storage-based unit commitment [29], and several others in recent years.

In this article, a bilevel optimal offering approach is presented for a joint wind farm–storage operating unit. In [30], various bilevel optimization problems and various approaches for solving them are reviewed. Various approaches have been introduced in recent research for solving bilevel optimization problems. In [31], a nested evolutionary scheme is used to solve a bilevel optimization problem. In [32], a Karush–Kuhn–Tucker (KKT) proximity measure is presented as a method for dealing with bilevel problems. For nonlinear bilevel optimization approaches, a penalty method with a trust-mechanism region is provided in [33]. Also, several new optimization models for power system problems are presented based on bilevel optimization. In [34], a bilevel optimization model is defined for the cyber-attack line overloading problem. Smart building connections to grids are modeled in [35] based on a bilevel optimization framework. To obtain a single-level objective, KKT conditions are written for the lower level optimization problem, which leads to mathematical programming with equilibrium constraints (MPEC) formulation. In the upper level, the profit is maximized according to the operational constraints of the storage system and the wind farm. In the lower level, the market-clearing problem is solved according to the submitted prices by generation units, wind farms, and the joint wind generation–storage unit.

According to the knowledge of the authors, an IGDT model that considers the uncertainties including wind generation, prices, and load concurrently is not developed for the MPEC optimal offering problem of a joint wind/storage unit. The main contributions of this article can be summarized as follows.

1) An MPEC modeled is presented for the joint operation of a wind farm and a storage unit. Various linearization techniques have been implemented to this problem to tackle different types of nonlinearity and obtain a linearized formulation.
2) A risk-averse strategy based on IGDT is presented for assuring a minimum amount of profit when the decision-maker has a pessimistic view of uncertain parameters including wind generation and submitted prices. Besides, an opportunity seeker strategy is also introduced for the bilevel optimal offering problem.
3) A multivariable IGDT scheme is developed for the simultaneous optimization of various uncertain variables deviation.

The remainder of this article is organized as follows. In Section II, problem model and formulation of the bilevel optimal offering of the joint unit are presented. Section III presents the IGDT method and the implementation to the optimal bidding problem of the joint unit. Numerical results and simulations are illustrated in Section IV. Finally, related conclusions are expressed in Section V.

II. Problem Formulation

In this article, strategic offers for a day-ahead market are submitted to the independent system operator (ISO) by the joint operating unit in a hierarchical structure. In the upper level, the joint unit, including wind farm and energy storage system, submits generation, charge, and discharge offers for each hour to the lower level, i.e., the ISO or market operator. The ISO not only receives offers from the joint unit, but also from other generation units, wind farms, and load aggregators. In the upper level, the optimization problem is solved to maximize the profit of the joint generation unit considering operational constraints of the storage system and limitations of wind generation. The lower level, which is the economic dispatch procedure, is regarded as a problem to minimize operating costs.

A. Mathematical Modeling

As mentioned, in the upper level, the profit maximization problem is solved according to

$$\max \sum_{t\in T} \lambda_i(t)\left(P_i^{Wj}(t) + P_{i,\mathrm{dis}}^S(t) - P_{i,ch}^S(t)\right) \quad \forall i \in S,\ \ \forall i \in Wj \tag{1}$$

$$s_{\mathrm{ch}}(t) + s_{\mathrm{dis}}(t) \le 1 \tag{2}$$

$$P_{\mathrm{ch}}^{\min}.\, s_{\mathrm{ch}}(t) \le P_{i,ch}(t) \le P_{\mathrm{ch}}^{\max}.\, s_{\mathrm{ch}}(t) \tag{3}$$

$$P_{\mathrm{dis}}^{\min}.\, s_{\mathrm{dis}}(t) \le P_{i,\mathrm{dis}}(t) \le P_{\mathrm{dis}}^{\max}.\, s_{\mathrm{dis}}(t) \tag{4}$$

$$E(t+1) = E(t) + P_{i,ch}(t)\,.\,\Delta t - P_{i,\mathrm{dis}}(t)\,.\,\Delta t \tag{5}$$

$$E_{\min} \le E(t) \le E_{\max} \tag{6}$$

$$0 \le P_i^{Wj}(t) \le P_{\max}^{Wj} \tag{7}$$

$$PP_{\mathrm{dis}}^{\max}(t) \le P_{\mathrm{dis}}^{\max}.\, s_{\mathrm{dis}}(t) \tag{8}$$

$$P_{\mathrm{dis}}^{\min}.\, s_{\mathrm{dis}}(t) \le PP_{\mathrm{dis}}^{\min}(t) \tag{9}$$

$$PP_{\mathrm{ch}}^{\max}(t) \le P_{\mathrm{ch}}^{\max}.\, s_{\mathrm{ch}}(t) \tag{10}$$

$$P_{\mathrm{dis}}^{\min}.\, s_{\mathrm{ch}}(t) \le PP_{\mathrm{ch}}^{\min}(t)\,. \tag{11}$$

In (1), the revenue of the joint generation unit is maximized according to the price of the bus that the joint unit is installed. Equation (2) prevents the simultaneous operation of the storage system in the charge and discharge state. In (3) and (4), the charge and discharge power are limited. The state of charge of the storage system is specified by (5) for each hour. Moreover, the amount of stored energy is limited by (6). Finally, the wind generation of the joint unit is constricted by (7). Equations (8)–(11) show the limitations for auxiliary variables that are used in the lower level problem for the storage system to avoid using binary variables in the lower level problem.

In addition to operational constraints, in the lower level, the economic dispatch problem is solved according to the received offers as indicated in (12)–(20) in the following:

$$\min \sum_{t\in T}\Bigg[\sum_{i\in G} x_i^G(t)\,.\,P_i^G(t) - \sum_{d\in D} b_i^d(t)\,.\,P_i^D(t) + \sum_{i\in W} c_i^W(t)\,P_i^W(t) + \gamma_i^{Wj}(t)\,P_i^{Wj}(t) + \gamma^{\mathrm{dis}}(t)\,.\,P_{i,\mathrm{dis}}^s(t) - \gamma^{\mathrm{ch}}(t)\,.\,P_{i,ch}^s(t)\Bigg] \tag{12}$$

$$P_i^G(t) - P_i^D(t) + P_i^W(t) + P_i^{Wj}(t) + P_{i,\mathrm{dis}}(t) - P_{i,ch}(t) = \sum_j H_{ij}\left(\delta_i(t) - \delta_j(t)\right) : \lambda_i(t) \tag{13}$$

$$P_i^{G,\min} \le P_i^G(t) \le P_i^{G,\max} : \alpha_{i,\min}^G(t),\ \alpha_{i,\max}^G(t) \tag{14}$$

$$P_i^{D,\min} \le P_i^D(t) \le P_i^{D,\max} : \alpha_{i,\min}^D(t),\ \alpha_{i,\max}^D(t) \tag{15}$$

$$P_i^{W,\min} \le P_i^W(t) \le P_i^{W,\max} :\ \alpha_{i,\min}^W(t),\ \alpha_{i,\max}^W(t) \tag{16}$$

$$0 \le P_i^{Wj}(t) \le P_i^{Wj,\max} : \alpha_{i,\min}^{Wj}(t),\ \alpha_{i,\max}^{Wj}(t) \tag{17}$$

$$PP_{\text{dis}}^{\min}(t) \le P_{i,\text{dis}}^{S}(t) \le PP_{\text{dis}}^{\max}(t) :\ \alpha_{\min}^{S,\text{dis}}(t),\ \alpha_{\max}^{S,\text{dis}}(t) \tag{18}$$

$$PP_{\text{ch}}^{\min}(t) \le P_{i,ch}^{S}(t) \le PP_{\text{ch}}^{\max}(t) :\ \alpha_{\min}^{S,ch}(t),\ \alpha_{\max}^{S,ch}(t) \tag{19}$$

$$-C_{ij} \le H_{ij}(\delta_i - \delta_j) \le C_{ij} :\ \alpha_{i,j,\min}^{L}(t),\ \alpha_{i,j,\max}^{L}(t). \tag{20}$$

In these relations, (12) minimizes the total operational cost while (13) shows the power balance for each bus. Relations (14)–(17) show the up and down limitations for the thermal units, loads, wind producers, and wind producers of the joint unit. Equations (18) and (19) show constraints for the discharge/charge operation of the storage unit. Finally, (20) indicates the line flow limits. The dual variable of each of these constraints is indicated by the colons of each relation.

To obtain a single-level optimization problem, the lower level optimization problem is replaced by the KKT conditions. The stationary constraints are as follows:

$$x_i^G(t) - \lambda_i(t) - \alpha_{i,\min}^G(t) + \alpha_{i,\max}^G(t) = 0 \tag{21}$$

$$-b_i^d(t) + \lambda_i(t) - \alpha_{i,\min}^D(t) + \alpha_{i,\max}^D(t) = 0 \tag{22}$$

$$c_i^W(t) - \lambda_i(t) - \alpha_{i,\min}^w(t) + \alpha_{i,\max}^w(t) = 0 \tag{23}$$

$$\gamma_i^{Wj}(t) - \lambda_i(t) - \alpha_{i,\min}^{Wj}(t) + \alpha_{i,\max}^{Wj}(t) = 0 \tag{24}$$

$$\gamma^{\text{dis}}(t) - \lambda_i(t) - \alpha_{\min}^{S,\text{dis}}(t) + \alpha_{\max}^{S,\text{dis}}(t) = 0 \tag{25}$$

$$-\gamma^{\text{ch}}(t) + \lambda_i(t) - \alpha_{\min}^{S,dch}(t) + \alpha_{\max}^{S,dch}(t) = 0 \tag{26}$$

$$\begin{aligned}&-\sum_{j>i} H_{ij}\left(\alpha_{i,j,\min}^L(t) - \alpha_{i,j,\max}^L(t)\right)\\ &+\sum_{j<i} H_{ij}\left(\alpha_{i,j,\min}^L(t) - \alpha_{i,j,\max}^L(t)\right) + \sum_{j\neq i} H_{ij}\lambda_i(t)\\ &-\sum_{j\neq i} H_{ij}\lambda_j(t).\end{aligned} \tag{27}$$

The complimentary constraints are indicated in the following:

$$0 \le \alpha_{i,\min}^G(t) \perp \left(P_i^G(t) - P_i^{G,\min}\right) \ge 0 \tag{28}$$

$$0 \le \alpha_{i,\max}^G(t) \perp \left(P_i^{G,\max} - P_i^G(t)\right) \ge 0 \tag{29}$$

$$0 \le \alpha_{i,\min}^D(t) \perp \left(P_i^D(t) - P_i^{D,\min}\right) \ge 0 \tag{30}$$

$$0 \le \alpha_{i,\max}^D(t) \perp \left(P_i^{D,\max} - P_i^D(t)\right) \ge 0 \tag{31}$$

$$0 \le \alpha_{i,\min}^W(t) \perp \left(P_i^W(t) - P_i^{W,\min}\right) \ge 0 \tag{32}$$

$$0 \le \alpha_{i,\max}^W(t) \perp \left(P_i^{W,\max} - P_i^W(t)\right) \ge 0 \tag{33}$$

$$0 \le \alpha_{i,\min}^{Wj}(t) \perp P_i^{Wj}(t) \ge 0 \tag{34}$$

$$0 \le \alpha_{i,\max}^{Wj}(t) \perp \left(P_i^{Wj,\max} - P_i^{Wj}(t)\right) \ge 0 \tag{35}$$

$$0 \le \alpha_{\min}^{S,\text{dis}}(t) \perp \left(P_{i,\text{dis}}^S(t) - PP_{\text{dis}}^{\min}(t)\right) \ge 0 \tag{36}$$

$$0 \le \alpha_{\max}^{S,\text{dis}}(t) \perp \left(PP_{\text{dis}}^{\max}(t) - P_{i,\text{dis}}^S(t)\right) \ge 0 \tag{37}$$

$$0 \le \alpha_{\min}^{S,ch}(t) \perp \left(P_{i,ch}^S(t) - PP_{\text{ch}}^{\min}(t)\right) \ge 0 \tag{38}$$

$$0 \le \alpha_{\max}^{S,ch}(t) \perp \left(PP_{\text{ch}}^{\max}(t) - P_{i,ch}^S(t)\right) \ge 0 \tag{39}$$

$$0 \le \alpha_{i,j,\min}^L(t) \perp \left(H_{ij}\left(\delta_i(t) - \delta_j(t)\right) + C_{ij}\right) \ge 0 \tag{40}$$

$$0 \le \alpha_{i,j,\max}^L(t) \perp \left(C_{ij} - H_{ij}\left(\delta_i(t) - \delta_j(t)\right)\right) \ge 0. \tag{41}$$

The obtained optimization problem is nonlinear due to (1) and (28)–(41). The linearization approach of relations (28)–(41) is described in [4] using the big-*M* approach. For (1), from (24)–(26) and (36)–([39), the following relation can be obtained:

$$\begin{aligned}&\lambda\left(P_i^{Wj}(t) + P_{i,\text{dis}}(t) - P_{i,ch}(t)\right)\\ &= \gamma_i^{Wj}(t)\, P_i^{Wj}(t) + \gamma^{\text{dis}}(t)\,.\, P_{i,\text{dis}}^s(t) - \gamma^{\text{ch}}(t)\,.\, P_{i,ch}^s(t)\\ &\quad + \alpha_{i,\max}^{Wj}(t)\, P_i^{Wj,\max} - \alpha_{\min}^{S,\text{dis}}(t)\, PP_{\text{dis}}^{\min}(t)\\ &\quad + \alpha_{\max}^{S,\text{dis}}(t)\, PP_{\text{dis}}^{\max}(t) - \alpha_{\min}^{S,ch}(t)\, PP_{\text{ch}}^{\min}(t)\\ &\quad + \alpha_{\max}^{S,ch}(t)\, PP_{\text{ch}}^{\max}(t)\end{aligned} \tag{42}$$

As the objective function is linear and the Slater condition is valid, strong duality can be written for this objective function as indicated in (43). From this relation and (42), the linearized objective function of (1) is equivalent to (44).

It is worth mentioning that to avoid binary variables in the lower level problem, auxiliary variables are utilized in (8)–(11). By using these variables, the charge and discharge power of the storage system will be restricted according to relations (18) and (19).

The final optimal joint unit offering problem is composed of the objective function (44), constraints (2)–(11), constraints (13)–(27), and linearized relations of (28)–(41)

$$\begin{aligned}&\sum_{i\epsilon G} x_i^G(t)\, P_i^G(t) - \sum_{i\epsilon D} b_i^d(t)\, P_i^D + \sum_{i\epsilon W} c_i^W(t)\, P_i^W(t)\\ &\quad + \gamma^{\text{dis}}(t)\, P_{\text{dis}}^s(t) - \gamma^{\text{ch}}(t)\, P_{\text{ch}}^s(t) + \gamma_i^{Wj}(t)\, P_i^{Wj}(t)\\ &\quad = \sum_{i\epsilon G}\left(\alpha_{i,\min}^G(t)\, P_i^{G,\min} - \alpha_{i,\max}^G(t)\, P_i^{G,\max}\right)\\ &\quad + \sum_{i\epsilon D}\left(\alpha_{i,\min}^D(t)\, P_i^{D,\min} - \alpha_{i,\max}^D(t)\, P_i^{D,\max}\right)\\ &\quad + \sum_{i\epsilon W}\left(\alpha_{\min}^W(t)\, P_i^{W,\min} - \alpha_{\max}^W(t)\, P_i^{W,\max}\right)\\ &\quad - \sum_{i,j\epsilon L}\left(\alpha_{i,j,\min}^L(t) + \alpha_{i,j,\max}^L(t)\right) C_{ij}),\\ &\quad - \alpha_{i,\max}^{Wj} P_i^{Wj,\max} + \alpha_{\min}^{S,\text{dis}} PP_{\text{dis}}^{\min}(t)\\ &\quad - \alpha_{\max}^{S,\text{dis}} PP_{\text{dis}}^{\max}(t) + \alpha_{\min}^{S,ch} PP_{\text{ch}}^{\min}(t)\\ &\quad - \alpha_{\max}^{S,ch} PP_{\text{ch}}^{\max}(t)\end{aligned} \tag{43}$$

$$
\begin{aligned}
Max \sum_{t\in T} \Bigg[& \sum_{i\in G} (\alpha_{i,\min}^{G}(t) P_i^{G,\min} - \alpha_{i,\max}^{G}(t) P_i^{G,\max}) \\
& + \sum_{i\in D} \left(\alpha_{i,\min}^{D}(t) P_i^{D,\min} - \alpha_{i,\max}^{D}(t) P_i^{D,\max}\right) \\
& + \sum_{i\in W} \left(\alpha_{i,\min}^{W}(t) P_i^{W,\min} - \alpha_{i,\max}^{W}(t) P_i^{W,\max}\right) \\
& - \sum_{i,j\in L} (\alpha_{i,j,\min}^{L}(t) + \alpha_{i,j,\max}^{L}(t)) C_{ij} \\
& - \sum_{i\in G} x_i(t) P_i^{G}(t) + \sum_{i\in D} b_i(t) P_i^{D} \\
& - \sum_{i\in W} c_i^{W}(t) P_i^{W}(t), \Bigg] \qquad (44)
\end{aligned}
$$

III. IGDT for Optimal Offering

A. IGDT Principles

Numerous approaches have been presented to overcome uncertainties in power system problems. These problems, e.g., probabilistic and stochastic approaches [36]–[39] are dependent on probabilistic historical data and are not applicable without accurate probability density functions. Hence, these approaches are not appropriate when sufficient historical data are not available [40].

Assume an optimization problem which is formulated as (45)–(48) where F is the objective function, γ and X are the uncertain and decision variables. $\boldsymbol{H}$ and $\boldsymbol{G}$ are the inequalities and equalities, respectively. S_{ieq}, S_{eq}, and Ω are the sets of inequalities, equalities, and uncertainties

$$\min F(X,\gamma) \qquad (45)$$

$$\boldsymbol{H}_i(X,\gamma) \le 0, \quad i \in S_{ieq} \qquad (46)$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \qquad (47)$$

$$\gamma \epsilon \Omega. \qquad (48)$$

The set of uncertainties can be defined as

$$\forall \gamma \,\epsilon\, \Omega(\bar{\gamma},\alpha) = \left\{ \gamma : \left| \frac{\gamma - \bar{\gamma}}{\gamma} \right| \le \alpha_{IGDT} \right\}. \qquad (49)$$

In (49), $\bar{\gamma}$ is the forecasted amount of uncertain parameter γ. α_{IGDT} shows the radius that the parameter can drift from the forecasted value and shows the robustness value for the risk averse strategy and the opportunity value for the opportunity seeking strategy.

For the IGDT approach initially, the objective function is solved according to forecasted uncertain parameters. In the next stage, the decision-maker can adopt two different strategies, including risk-averse and opportunity-seeking strategies. In the next section, each of these strategies is described.

1) Risk-Averse Strategy: In this strategy, the decision-maker tries to provide solutions to guarantee a specified amount of profit against a maximum deviation of an uncertain variable from the forecasted amount.

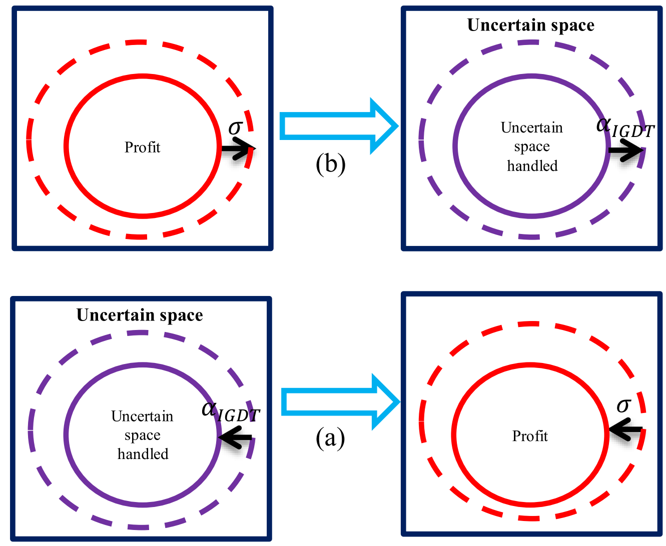

Fig. 1. Concept of IGDT. (a) Risk-averse strategy. (b) Opportunity-seeking strategy.

In this strategy, when the specified uncertain parameter is assumed to be at the extreme point, the most robust and conservative solutions will be obtained. The formulation of this strategy is as follows:

$$\max \alpha_{IGDT} \qquad (50)$$

$$\boldsymbol{H}_i(X,\gamma) \le 0, \quad i \in S_{ieq} \qquad (51)$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \qquad (52)$$

$$F(X,\gamma) \ge (1-\sigma) . F_0(X,\bar{\gamma}) \qquad (53)$$

$$\gamma = (1-\alpha_{IGDT}) . \bar{\gamma}. \qquad (54)$$

In (48), σ is the deviation factor. $F_0(X,\bar{\gamma})$ is the objective function corresponding to the forecasted values of the uncertain variables $\bar{\gamma}$. To better indicate the concept of the risk-averse strategy for the IGDT method, Fig. 1(a) is presented. In this figure, the solid lines are for the forecasted variables and the dashed circle shows the uncertain parameter variation. Also, the solid right on the left shows the base profit and the dashed circle shows the profit affected by the uncertainty. As it is obvious, for a certain uncertainty budget σ, it is indicated how much the uncertain parameter α_{IGDT} can decrease (or increase) to assure the minimum profit.

2) Opportunity-Seeking Strategy: In this strategy, the decision-maker is optimistic about uncertain variables and tries to increase the profit more than the base profit which is obtained according to the forecasted parameters. In a single objective optimization problem, this strategy can be formulated as follows:

$$\min \alpha_{IGDT} \qquad (55)$$

$$\boldsymbol{H}_i(X,\gamma) \le 0, \quad i \in S_{ieq} \qquad (56)$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \qquad (57)$$

$$F(X,\gamma) \ge (1+\sigma) . F_0(X,\bar{\gamma}) \qquad (58)$$

$$\gamma = (1 + \alpha_{IGDT}) \, . \, \bar{\gamma}. \tag{59}$$

In this formulation, (58) represents the profit increase that the decision-maker is seeking for the uncertain variables modeled in (44). Fig. 1(b) shows the concept of this strategy.

B. Implementation of IGDT to Optimal Offering Problem

The uncertain parameters for the optimal offering problem are assumed to be wind generation of the joint unit, prices offered by generation units, and the load of the system. To avoid nonlinearities, instead of obtaining robustness and opportuneness values for different uncertainty budgets, the uncertainty budget is obtained for different robustness and opportuneness values.

For wind generation uncertainty, the risk-averse strategy formulation is as follows:

$$\max \; (1 - \sigma) \, . \, \text{Profit}_0 \tag{60}$$

$$P_i^{Wj}(i,t) \le (1 - \alpha_{IGDT}) \, P_i^{Wj,\max} \tag{61}$$

$$0 \le \alpha_{i,\max}^{Wj}(t) \perp \left((1 - \alpha_{IGDT}) \, P_i^{Wj,\max} - P_i^{Wj}(t) \right) \ge 0 \tag{62}$$

$$\text{s.t. (2)–(7), (9)–(34), (36)–(41), (43).} \tag{63}$$

In addition, the opportunity seeker strategy formulation for this case is as follows:

$$\max \; (1 + \sigma) \, . \, \text{Profit}_0 \tag{64}$$

$$P_i^{Wj}(t) \le (1 + \alpha_{IGDT}) \, P_i^{Wj,\max} \tag{65}$$

$$0 \le \alpha_{i,\max}^{Wj}(t) \perp \left((1 + \alpha_{IGDT}) \, P_i^{Wj,\max} - P_i^{Wj}(t) \right) \ge 0 \tag{66}$$

$$\text{s.t. (2)–(7), (9)–(34), (36)–(41), (43).} \tag{67}$$

For the prices offered by generation units, the price will be multiplied by $(1 \pm \alpha_{IGDT})$. However, in the objective function, this will lead to a nonlinear term $(1 \pm \alpha_{IGDT}) P_i^G(t)$. To avoid this nonlinear term, for the price and load uncertainty studies, instead of considering the uncertainty budget as a parameter and the robustness/opportuneness value as a variable, the uncertainty budget is assumed as a variable while the robustness/opportuneness value is regarded as a constant parameter. Hence, for each constant robustness/opportuneness value, the corresponding uncertainty budget can be obtained. In the formulations for risk-averse and opportunity seeker strategy for price and load uncertainty, the constant robustness/opportuneness value α_{cte} is multiplied to the price and load parameters in relations (2)–(7), (9)–(34), (36)–(41), and (43). For a better understanding of how the IGDT approach is implemented to the joint wind/storage optimal offering approach, a flowchart is provided in Fig. 2 which indicates the process of the proposed model.

IV. Case Study and Discussion

In this section, numerical results are presented for evaluating the performance of the suggested method. A 60-MW wind farm and a 60-MWh (20-MW) storage system participate in the energy market as a joint unit at bus 15 of the IEEE 30-bus system. It is assumed that this system consists of nine thermal generation units at bus 1, 2, 5, 8, 11, 13, 15, 24, and 30. The generator offers are used from [4]. Also, a wind generation unit with a size of 40 MW is placed on bus 17. The maximum (minimum) charge/discharge rate of the storage system is assumed to be 20 MW (5 MW). The discharge (charge) price is assumed to be \$25 (\$25) for all hours. Also, the price of the wind farms is assumed to be \$25 at bus 15 and \$35 on bus 17 for 24 h. Also, in this article, it is assumed that loads are parameters and their values are determined according to the forecasted values. The M parameter is assumed to be 1×10^3 for thermal generation unit constraints and 1×10^7 for other complementary constraints. The MILP formulation is solved using an *hp pavilion* with a 2.1-GHz processor with 4 GB RAM using the CPLEX 9.0 solver in the GAMS environment [41].

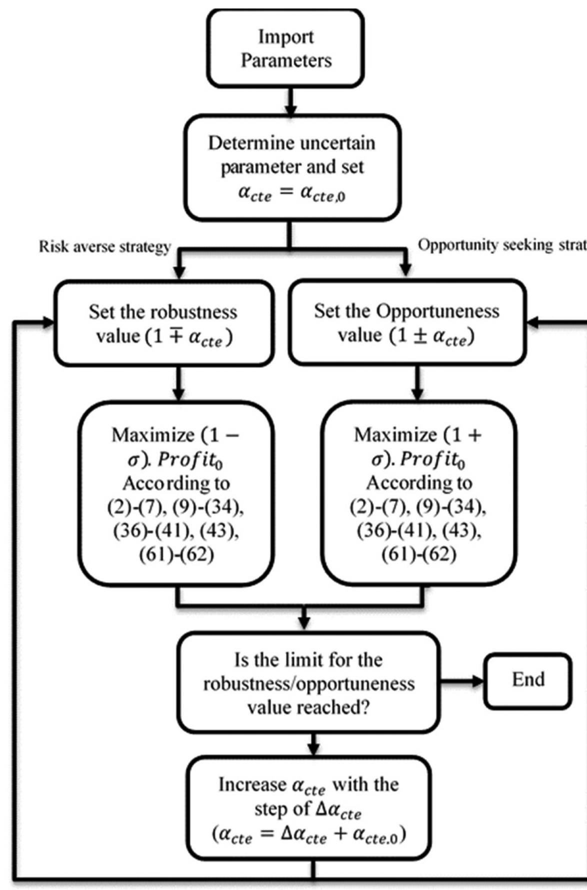

Fig. 2. Flowchart for the proposed optimal offering approach.

The studies are fulfilled for two different strategies assuming that for the first hour and last hour, the storage system has the minimum state of charge 10 MWh. For each of the uncertain variables, two different strategies including risk-averse strategy and opportunity seeker strategy are studied.

To have a simple case study, initially, the simulations are presented for the base case where the bilevel optimal offering problem is solved according to the forecasted parameters of

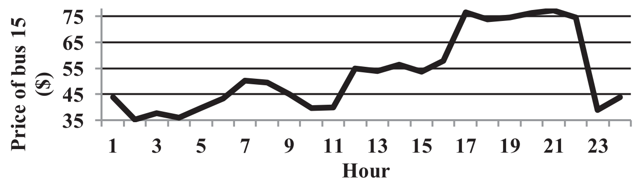

Fig. 3. Nodal prices at bus 15 for base case study neglecting uncertainties.

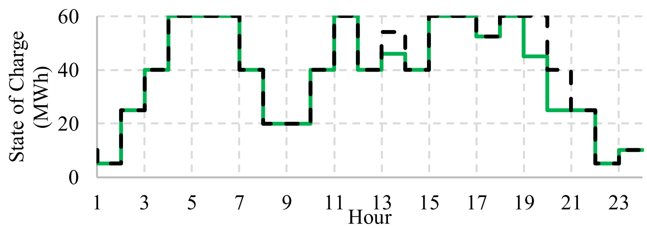

Fig. 4. State of charge of storage system for joint offering (green continuous) and solo storage system (black dashed).

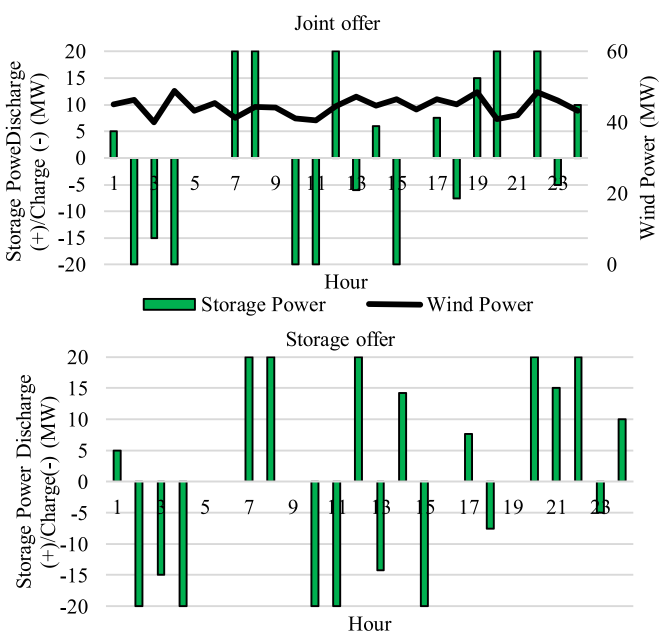

Fig. 5. Optimal power offer for the joint unit and the alone storage unit.

wind, price, and load, and all uncertainties are ignored. The total profit for this case is \$60 109. The profits of the wind unit and storage system individually for this case are \$57 463 and \$2646, respectively. The nodal price on bus 15 is indicated in Fig. 3. For this case, the results for the storage system outputs, including the stored energy and charge and discharge power for each hour and the power produced by the wind generation unit for 24 h, are illustrated in Figs. 4 and 5. As the results indicate, although in the joint offering case the income of the storage system decreases, the revenue of the wind farm and the revenue of the total system increases.

In the second case, the bilevel optimal offering problem is only considered for the energy storage system and the wind farm is considered as an independent unit. In this case, the storage unit income increases to \$3081 while the income of the wind generation unit decreases to \$57 038. In this case also, the state of charge of the storage system and the power for each hour are illustrated in Figs. 4 and 5, respectively.

TABLE I
IMPACT OF THE PRICE OFFERS

Offer price (\$/MWh)	Storage profit (\$)	Wind farm profit (\$)	Total profit (\$)	Wind power for 24 hours (MW)
25	26646	57463	60109	1070
45	2983	43612	46595	717
55	2999	27940	30939	405
75	3116	20784	23900	272

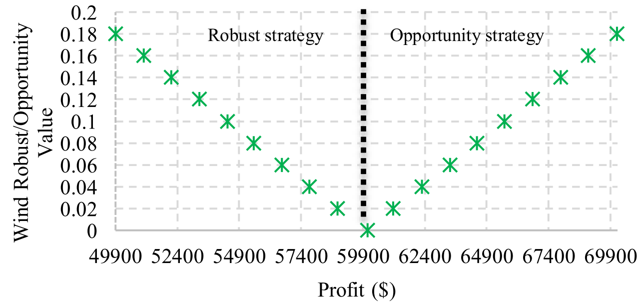

Fig. 6. Robustness value versus joint unit profit for stand-alone wind unit and joint unit.

Compared with nodal prices at bus 15 (indicated in Fig. 3), it is observed that the storage system is fully charged at hours when the price of energy is lower and starts discharging during hours when the price of energy is expensive with the goal of acquiring the maximum profit.

Also to study the effect of the price offers, Table I is provided, which includes the wind power price and charge/discharge power price for the joint unit (all the prices are assumed to be similar). In addition, this table indicates the revenue obtained by wind power, storage, total profit, and the total wind generation for 24 h. As it is obvious, by increasing the offering prices, the revenue of the system and also the wind power participation decreases, and the system moves toward the state that the storage system participates individually in the day-ahead market.

According to the base case, two different strategies are studied in the next sections.

A. *Wind Generation Uncertainty*

1) Risk-Averse Strategy: In this strategy, the owner practices a conservative approach to guarantee a minimum amount of profit considering the uncertainty of the wind farm. The robustness values versus the unit profit are exposed in Fig. 6 for $\sigma = 2\%–18\%$ and for two different cases including the stand-alone operation of the wind farm and the joint operation case. As it is obvious, the variation of the joint unit profit with the robustness value is almost linear.

This figure shows how much profit is guaranteed $(1-\sigma)\text{Profit}_0$ for a specific amount of wind generation reduction according to the forecasted values. For instance, to assure 84% of the profit at the base case, wind generation can be decreased to 16% at the joint operation case (\$50 484). In other words, for all hours, the wind generation can decrease by 16% while 84% of the base case profit is guaranteed.

From Fig. 6, it is observed that the variations of the robustness value are almost linear. To show the impact of the storage system on handling uncertainties caused by wind, the optimal offering problem is solved considering a minimum profit of \$46 801, that is, the obtained profit for the stand-alone wind generation unit with a robust value of 18%. In this case, the robustness value increases to 23.5%. Also, while an 18% robustness value guarantees approximately \$46 801 profit for the stand-alone wind generation unit, operating jointly results in an approximately \$49 924 profit for the same robustness value.

2) Opportunity Seeker Strategy: In this case study, the decision-maker adopts an optimistic strategy assuming that the wind generation will be above the predicted values for each hour. For this case, the opportuneness versus the minimum profit is depicted in Fig. 6.

Similar to the robustness strategy, there is a linear relation between the opportuneness value and the minimum acquired profit. As in the previous case, the effect of the storage system can be estimated from this figure. For instance, while an 18% increase in wind generation is required to achieve a minimum profit of \$67 185 in the wind farm stand-alone state, in the joint operation state, an increase of less than 12.5% is enough to acquire this amount of profit.

B. Price and Load Uncertainty

In this section, the uncertainty of prices offered by generation units and load forecasts are studied. To implement the IGDT method, the proposed approach introduced in the previous section is utilized to avoid nonlinear terms. Similar to wind generation uncertainty, results for two different strategies are presented in this section for each of these uncertainties.

1) Risk-Averse Strategy: Results for adopting the risk-averse strategy, considering the uncertainty of price, are illustrated in Fig. 7(a). Like the previous case, the robustness value decreases almost linearly with decreasing the minimum assured profit. For an uncertainty budget of 19.3%, even for a 20% reduction of offering prices by generation units, a profit of \$48 081 is certain.

For each of the minimum profit studying cases, the wind farm offers the maximum forecasted generation and the variation in results is caused by price and the different charge/discharge patterns of the storage system. The charge/discharge pattern of the storage system is depicted in Fig. 7(b) for $\sigma = 18\%$ for both robust and opportunity strategies.

Fig. 8 indicates the results for the robust strategy for load forecast variations. As it is obvious, load reduction has a trivial effect on the obtained profit.

2) Opportunity-Seeking Strategy: In this section, results for the opportunity-seeking strategy for price offers of generation

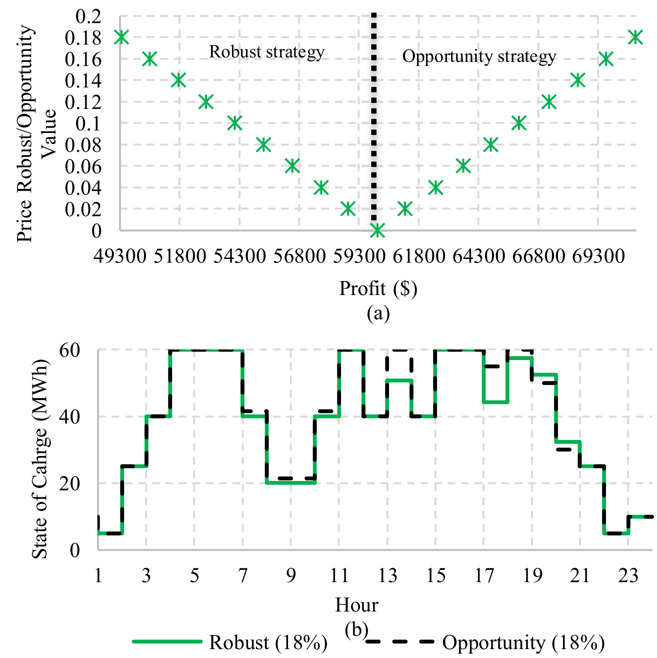

Fig. 7. (a) Results for considering price offer uncertainty (submitted by generation units) for robust and opportunity strategies. (b) State of charge for $\sigma = 18\%$ robust strategy (green solid) and $\sigma = 18\%$ opportunity strategy (black dashed) for the risk-averse strategy for price uncertainty.

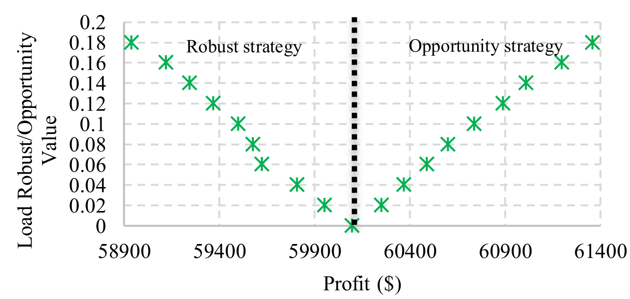

Fig. 8. Results for considering price offer uncertainty (submitted by generation units).

units are indicated in Fig. 7(a). As shown in this figure, a profit near \$72 918 can be achieved if the offered prices increase to 18%. The charge/discharge profiles for the extreme points of both strategies are shown in Fig. 7(b). Similar to the robust strategy, the increase of load in the opportuneness strategy does not affect the gained profit significantly, as illustrated in Fig. 8.

C. Multivariation Optimal Offering Based on IGDT

In this section, the results are presented when the deviating factors for wind and price are assumed to deviate simultaneously for acquiring a minimum amount of profit.

The multidimension robustness value (for wind generation and price uncertainty) is exposed in Fig. 9. As it is obvious, the obtained profit (which is a function of the uncertainty budget)

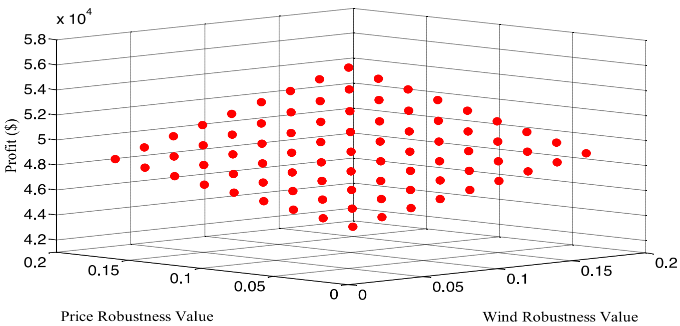

Fig. 9. Multivariant IGDT for wind and price uncertainty (risk-averse strategy).

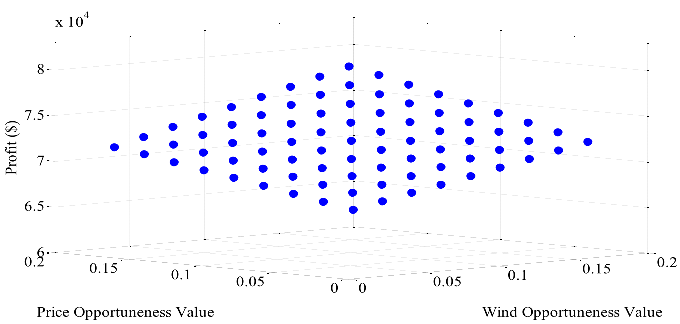

Fig. 10. Multivariant IGDT for wind and price uncertainty (opportunity-seeking strategy).

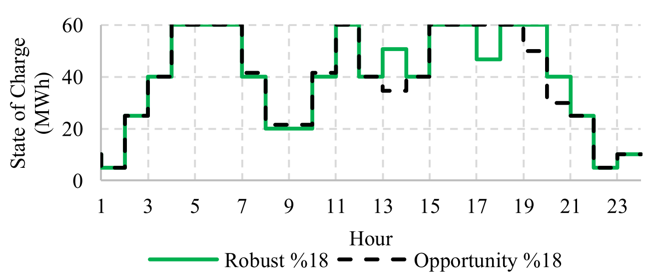

Fig. 11. State of charge for the multiobjective case wind and price robust strategy 18% (green continuous) and opportunity strategy 18% (black dashed).

forms a plain of solutions. In this figure, it is indicated that, for instance, if the wind generation and the offered prices decrease by 18%, a profit of \$41 035 is guaranteed. Further, Fig. 10 shows the multidimension case for the opportuneness strategy. Similar to the robust strategy, a plain of solutions are presented for this case. In this case, for an increase in wind generation and offered prices for 18%, the total profit increases to \$82 762. Fig. 11 shows the state of charge variation for these two mentioned cases.

V. Conclusion

In this article, a bilevel optimal offering approach is proposed for a joint wind–storage unit. In the upper level, the profit maximization problem is solved considering the operational constraints of the wind and storage unit. In the lower level, the economic dispatch problem is regarded. The bilevel problem is converted to a single-level optimization problem by implementing the KKT conditions. For the base case (based on the forecasted parameters), the results show that the total revenue of the joint unit is more than the state when the wind unit and storage unit work individually.

By the proposed framework, the decision-maker is able to study the effect of uncertainties caused by prices offered by generation units, generation of the joint wind farm, and system load variations. The results indicate that despite load uncertainty, the variations of wind generation and price offers can have a salient impact on the expected revenue of the joint unit on the offers and the expected profit. By utilizing this model, the decision-maker can have a control on the variations of uncertain variables in real time and guarantee a certain amount of profit, or to consider these uncertainties as an opportunity to gain additional revenue compared to the expected value. Further, the decision-maker can study how it can affect the system prices according to the offers that are submitted by the joint working unit regarding the lower level optimization problem. Finally, by using the provided multiobjective model, the effects of wind and price uncertainties can be studied concurrently to acquire the best profit according to the chosen strategy.

For future research, the possibility of solving the bilevel optimal offering strategy problem by evolutionary algorithms can be considered. When utilizing this type of approach, no linearizing techniques are required. Hence, several binary variables (which have to be used to obtain a linearized model) can be eliminated, which decreases the computational burden of the problem. Assuming other objective functions for the bilevel optimal offering problem and implementing multiobjective functions can also be considered for future work.

Furthermore, new bidding strategy approaches are developed nowadays based on approaches, such as automated negotiation and reinforcement learning, and their possibilities to be implemented in the strategic bidding problem of a wind/storage unit can be studied and the results can be compared with the bilevel offering approach in terms of the obtained profit and computational time. Developing the proposed model in this article for the joint offer of wind farms with electric vehicle charge stations can be another possibility for future research.

References

[1] D. Kirschen and G. Strbac, *Fundamentals of Power System Economics*. Hoboken, NJ, USA: Wiley, 2004.
[2] A. M. Jafari, H. Zareipour, A. Schellenberg, and N. Amjady, "The value of intra-day markets in power systems with high wind power penetration," *IEEE Trans. Power Syst.*, vol. 39, no. 3, pp. 1121–1132, May 2014.
[3] V. Kaminski, *Energy Markets*. London, U.K.: Risk Books, 2012.
[4] J. Wang, M. Shahidehpour, and Z. Li, "Security-constrained unit commitment with volatile wind power generation," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1319–1327, May 2008.
[5] D. Pozo, J. Contreras, and E. E. Sauma, "Unit commitment with ideal and generic energy storage units," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2974–2984, Nov. 2014.
[6] *Global Wind Energy Council*. [Online]. Available: http://www.gwec. net/
[7] L. Baringo and A. Conejo, "Offering strategy of wind power producer: A multi-stage risk-constrained approach," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1420–1429, Mar. 2016.

[8] H. Rashidizadeh, M. Vahedipour, M. Shafie-khah, and J. Catalao, "A bi-level risk constrained offering strategy of a wind power producer considering demand side resources," *Int. J. Elect. Power Energy Syst.*, vol. 104, pp. 562–574, 2019.
[9] H. Mohsenian-Rad, "Coordinated price-maker operation of large energy storage units in nodal energy markets," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 786–797, Jan. 2016.
[10] H. Ding, Z. Hu, and Y. Song, "Rolling optimization of wind farm and energy storage system in electricity markets," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2676–2684, Oct. 2014.
[11] H. Akhavan-Hejazi and H. Mohsenian-Rad, "Optimal operation of independent storage systems in energy and reserve markets," *IEEE Trans. Smart Grid*, vol. 2, no. 5, pp. 1088–1097, Mar. 2014.
[12] J. Garcia-Gonzalez, R. Moraga, L. M. Santos, and A. M. Gonzalez, "Stochastic joint optimization of wind generation and pumped-storage units in an electricity market," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 460–468, May 2008.
[13] D. Krishnamurty, C. Uckun, Z. Zhou, P. Thimmapuram, and A. Botterud, "Energy storage arbitrage under day-ahead and real-time price uncertainty," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 84–93, Jan. 2018.
[14] H. Cui, F. Li, H. Chen, and H. Wang, "Bilevel arbitrage potential evaluation of grid-scale energy storage considering wind power and LMP smoothing effect," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 707–718, Apr. 2018.
[15] K. Pandzic, H. Pandzic, and I. Kuzle, "Virtual storage plant offering strategy in the day-ahead electricity market," *Int. J. Elect. Power Energy Syst.*, vol. 104, pp. 401–413, 2019.
[16] K. Hartwig and I. Kockar, "Impact of strategic behavior and ownership on energy storage on provision of flexibility," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 744–754, Apr. 2016.
[17] A. Shahmohammadi, R. Sioshansi, A. Conejo, and S. Afsharnia, "Market equilibria and interactions between strategic generation, wind, and storage," *Appl. Energy*, vol. 220, pp. 876–92, 2018.
[18] E. Nasrolahpour, J. Kazempour, H. Zareipour, and W. Roserhart, "A bilevel model for participation of a storage system in energy and reserve markets," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 582–598, Apr. 2018.
[19] E. Kardakos, C. Simoglu, and A. Bakirtzis, "Optimal offering strategy of virtual power plant: A stochastic bilevel approach," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 794–806, Mar. 2016.
[20] Z. Liang and Y. Guo, "Robust optimization-based bidding strategy for virtual power plants in electricity markets," in *Proc. IEEE Power Energy Soc. General Meeting*, Boston, MA, USA, 2016, pp. 1–5.
[21] M. Kazemi, H. Zareipour, N. Amjady, W. Rosehart, and M. Ehsan, "Operation scheduling of battery storage systems in joint energy and ancillary services markets," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1726–1735, Mar. 2019.
[22] S. Nojavan, A. Akbari-Dibavar, and K. Zare, "Optimal energy management of compressed air energy storage in day-ahead and real-time energy markets," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 16, pp. 3673–3679, Aug. 2019.
[23] A. Dolatabadi, M. Jadidbonab, and B. Mohammadi-Ivatloo, "Short-term scheduling strategy for wind-based energy hub: A hybrid stochastic/IGDT approach," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 438–448, Jan. 2019.
[24] B. M. Ivatloo and B. N. Heris, *Robust Optimal Planning and Operation of Electrical Energy Systems*. Basel, Switzerland: Springer, 2019.
[25] M. Majidi, B. Mohammadi-Ivatloo, and A. Soroudi, "Application of information gap decision theory in practical energy problems: A comprehensive review," *Appl. Energy*, vol. 249, pp. 157–165, 2019.
[26] N. Rezaei, A. Ahmadi, A. Khazali, and J. Aghaei "Multiobjective risk-constrained optimal bidding strategy of smart microgrids: An IGDT-based normal boundary intersection approach," *IEEE Trans. Ind. Inform.*, vol. 15, no. 3, pp. 1532–1543, Mar. 2018.
[27] A. Khazali, N. Rezaei, A. Ahmadi, and B. Hredzak, "Information gap decision theory based preventive/corrective voltage control for smart power systems with high wind penetration," *IEEE Trans. Ind. Inform.*, vol. 14, no. 10, pp. 4385–4394, Oct. 2018.
[28] N. Rezaei, A. Ahmadi, A. Khazali, and J. M. Guerrero, "Energy and frequency hierarchical management system using information gap decision theory for islanded microgrids," *IEEE Trans. Ind. Electron.*, vol. 65, no. 10, pp. 7921–7932, Oct. 2018.
[29] A. Ahmadi, A. E. Nezhad, and B. Hredzak, "Security-constrained unit commitment in presence of lithium-ion battery storage units using information-gap decision theory," *IEEE Trans. Ind. Inform.*, vol. 15, no. 1, pp. 148–157, Jan. 2019.
[30] A. Sinha and K. Deb, "A review on bilevel optimization: From classical to evolutionary approaches and applications," *IEEE Trans. Evol. Comput.*, vol. 22, no. 2, pp. 276–294, Apr. 2018.
[31] H. K. Singh, M. M. Islam, T. Ray, and M. Ryan, "Nested evolutionary algorithms for computationally expensive bilevel optimization problems: Variants and their systematic analysis," *Swarm Evol. Comput.*, vol. 48, pp. 329–344, Aug. 2019.
[32] A. Sinha, T. Soun, and K. Deb, "Using Karush-Kuhn-Tucker proximity measure for solving bilevel optimization problems," *Swarm Evol. Comput.*, vol. 44, pp. 496–510, Feb. 2019.
[33] B. El-Sobky and Y. Abo-Elnaga, "A penalty method with trust-region mechanism for nonlinear bilevel optimization problem," *J. Comput. Appl. Math.*, vol. 340, pp. 360–374, Oct. 2018.
[34] Y. Tan, Y. Cao, and M. Shahidehpour, "Cyber-attach on overloading multiple lines: A bilevel mixed-integer linear programming model," *IEEE Trans. Smart Grids*, vol. 2, no. 9, pp. 1534–1536, Aug. 2018.
[35] M. Razmara, G. Bharati, M. Shahbakhti, S. Paudyal, and R. Robinett, "Bilevel optimization framework for smart building to grid systems," *IEEE Trans. Smart Grids*, vol. 2, no. 9, pp. 582–593, Mar. 2018.
[36] M. Alipour, B. Mohammadi, and K. Zare, "Stochastic scheduling of renewable and CHP-based microgrids," *IEEE Trans. Ind. Inform.*, vol. 11, no. 5, pp. 1049–1058, Jun. 2015.
[37] M. Zare, T. Niknam, R. Azizipanah, and A. Ostadi, "New stochastic bi-objective optimal cost and chance of operation management approach for smart microgrid," *IEEE Trans. Ind. Inform.*, vol. 12, no. 6, pp. 2031–2040, Dec. 2016.
[38] H. Khorramdel, J. Aghaei, B. Khorramdel, and P. Siano, "Optimal battery sizing in microgrids using probabilistic unit commitment," *IEEE Trans. Ind. Inform.*, vol. 12, no. 2, pp. 834–843, Apr. 2016.
[39] J. Aghaei, A. Baharvandi, A. Rabiee, and M. Akbari, "Probabilistic PMU placement in electric power networks: An MILP-based multi-objective model," *IEEE Trans. Ind. Inform.*, vol. 11, no. 2, pp. 332–341, Jan. 2015.
[40] C. Murphy, A. Soroudi, and A. Keane, "Information gap decision theory-based congestion and voltage management in the presence of uncertain wind power," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 841–849, Jul. 2017.
[41] A. Brooke, D. Kendrick, A. Meeraus, and R. Raman, *GAMS/CPLEX: A User's Guide*. WA, DC, USA: GAMS, 2003.

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