A Mixed CVaR-Based Stochastic Information Gap Approach for Building Optimal Offering Strategies of a CSP Plant in Electricity Markets

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This work was supported in part by the National Key Research and Development Program of China under Grant 2016YFB0901100, and in part by the National Natural Science Foundation of China under Grant 51777185.

ABSTRACT The development of the concentrating solar power (CSP) plant as a new dispatchable resource that can participate in the electricity markets as an independent power producer and coordinate intermittent renewables has attracted much attention recently. In this work, optimal offering strategies of a price-taker CSP plant in the day-ahead (DA) and real-time (RT) electricity markets are addressed considering non-stochastic uncertainties (NSUs) from the thermal production of the CSP plant and stochastic uncertainties (SUs) from the market prices as well as the risk attitude of the CSP plant concerned. A hybrid stochastic information gap approach (SIGA) integrating the well-established information gap decision theory with the mixed conditional value at risk (CVaR) is proposed to hedge the revenue risk against NSUs and SUs in the offering problem based on the risk preference of the decision maker. A two-stage architecture is utilized for framing the DA and RT offering problems, where the first-stage co-optimizes offering strategies in the DA and RT markets, while the second-stage determines the actual RT hourly offering strategy in a rolling horizon manner. Case studies show that the SIGA can make optimal offering strategies against the non-stochastic thermal production and stochastic market prices given the risk attitude of the CSP plant. Comparisons also demonstrate that the SIGA could be an effective tool to manage coexistent NSUs and SUs.

INDEX TERMS Concentrating solar power (CSP), information gap decision theory (IGDT), mixed conditional value at risk, offering strategy, risk hedging, uncertainty management.

NOMENCLATURE
A. SUBSCRIPT INDEXES AND SET
$h, t$ Subscript index of hour.
$T$ Set of hours, with cardinality $|T| = 24$, $T = \{1, 2, \ldots, 24\}$.
$s$ Index of scenario.
$m$ Set of subscript index, i.e., $m = \{I, II\}$, with $I/II$ for the first/second-stage matrices or vectors.

B. PARAMETERS
$p_{\text{min}}/p_{\text{max}}$ Lower/upper limit of electric power output of the CSP plant, in megawatts-electric (MW-e).
$p_{\text{dmax}}$ Ramping down limit of the CSP plant, in MW-e.
$c_{\text{vc}}$ Variable cost of the CSP plant, in $/\text{MW-e}$.
$q_{\text{min}}/q_{\text{max}}$ Lower/upper storage limit of thermal energy storage (TES), in megawatts-thermal-hour (MW-t·h).
$q_{\text{final}}$ Required thermal energy of TES at the end of the operating day, in MW-t·h.
$p_{\text{chmax}}$ Maximum charging power of TES, in MW-t.
$\eta_{\text{dc}}/\eta_{\text{ch}}$ Discharging/charging efficiency of TES, in $\%$.
$\eta_{\text{te}}$ Thermal-electric efficiency of power block, in $\%$.
$r$ Hourly thermal loss factor of TES, in $\%$.
$p_{\text{stup}}^h$ Startup power of the CSP plant, in MW-t.

The associate editor coordinating the review of this manuscript and approving it for publication was Dwarkadas Pralhaddas Kothari.
\( p_{\text{sp}} \) Required startup energy of the CSP plant, in MW-t.h.

\( e_{\text{m}}/\delta_{\text{m}} \) Robust/opportunistic revenue threshold factor, in \%.

### C. VARIABLES

- \( y_h^{DA} \) Predicted DA market price, in $/MW-e.
- \( y^RT_h \) Predicted RT market price, in $/MW-e.
- \( P_{h}^{\text{SP}} \) Predicted thermal production of solar field, in MW-t.
- \( P_h^{DA} \) DA offering quantity of the CSP plant, in MW-e.
- \( P_h^{RT} \) RT offering quantity of the CSP plant, in MW-e.
- \( P_{h}^{\text{E}} \) Electric power output of the CSP plant, in MW-e.
- \( P_{h}^{\text{Pb}} \) Thermal power input of the power block, in MW-t.
- \( p_{h}^{ch}/p_{h}^{dc} \) Charging/discharging power of TES from solar field/to power block, in MW-t.
- \( \rho_{h}^{\text{SP}} \) Power spillage of the CSP plant, in MW-t.
- \( v_h \) Binary variable. 1 means power block is in operation; 0 otherwise.
- \( u_{h}^{\text{on}}/u_{h}^{\text{off}} \) Binary variable. 1 means power block is started up/shut down; 0 otherwise.
- \( T_{h}^{\text{on}}/T_{h}^{\text{off}} \) Minimum online/offline time of power block, in h.
- \( Q_{h}^{\text{st}}/T_{h}^{\text{dc}} \) Stored thermal energy of TES, in MW-t.h.
- \( x \) Decision vector for the first-stage offering model, \( x = [(x_1^{DA})^T; (x_1^{RT})]^T = [P_1^{DA}, \ldots, P_1^{RT}; \ldots; P_N^{DA}, \ldots, P_N^{RT}]^T \).
- \( y_{h,t} \) Decision vector for the second-stage offering model from hour \( h \) to \( y_{h,t} = [P_{h}^{\text{RT}}, P_{h+1}^{\text{RT}}, \ldots, P_{T}^{\text{RT}}] \), where \( t > h \).
- \( u_{m}/u_{m} \) Vector of actual/predicted NSUs.
- \( e_{m}/\bar{e}_{m} \) Vector of SUs at scenario \( s \) of predicted SUs.
- \( e_{m}(\xi) \) Vector function of stochastic variable \( \xi \).
- \( \kappa_{m}/\delta_{m} \) Uncertainty horizon of the robust/opportunistic model, in p.u.
- \( \pi \) Pessimism coefficient of the Hurwicz’s criterion.
- \( \theta \) Quantile of the CVaR, or mixed CVaR, in \%.
- \( Y_{m,s} \) Probability of scenario \( s \).
- \( f_{m}^{RA0} \) Robust revenue threshold, in $.
- \( f_{m}^{RS0} \) Opportunistic revenue threshold, in $.
- \( f_{m}^{RO} \) Revenue determined by predicted NSUs, in $.
- \( f_{m}^{f} \) Auxiliary variable for calculating CVaR, in $.

## I. INTRODUCTION

During the past two decades, the development of the concentrating solar power (CSP) technology as one of the prospective solutions to environment problems and fossil energy crises has been paid much attention [1], [2]. A CSP plant can generate electricity via its power block using the solar thermal energy collected from solar radiations [3]. Since the CSP plant is environment-friendly and dispatchable, it is recognized as one of the most promising generation technologies worldwide [4].

Researches on the operations of CSP plant have centered on scheduling strategies, transmission planning in power systems with high share of renewables, and collaborative operation with other renewable and responsive loads [5], in order to maximize economic benefits of not only the CSP plant but also the concerned power system, to mitigate fluctuations and variabilities of intermittent power sources, and to accommodate more renewable generation while not undermining the power system reliability [6].

The optimal scheduling strategies of CSP plants under the market environment have been widely studied in the literature. In [3], in order to maximize the revenue, the operation of a CSP plant in the day-ahead (DA) spot market is investigated using perfect predictions of market prices and thermal productions. In [7], a linear offering model for a CSP plant is presented using robust optimization (RO) and stochastic programming (SP) to deal with uncertainties from solar resources and market prices, respectively. In [8], a DA offering model for the CSP plant in the energy, regulation and reserve markets is proposed, in which the uncertainties are managed as in [7]. In [9], the generation scheduling of the CSP plants in the DA market is addressed using the model predictive control technique. In [10], a mixed-integer linear programming model for the DA scheduling optimization of the CSP plants is proposed to not only maximize the DA revenue but also minimize the generation cycling. In [11], a risk-constrained stochastic offering optimization model for a CSP plant is presented using the downside risk constraints and formulated as mixed integer linear programming. In [12], the DA coordinated operation and scheduling strategies for wind farms and CSP plants in the energy and spinning reserve markets are proposed. In [13], based on the \( N-k \) security constraint, a DA harmonious scheduling strategy between wind farms and CSP plants is proposed and formulated as a bi-level model, where the upper-level model aims at scheduling the energy and spinning reserve while the lower-level one searching the outage plants. In [14], the DA scheduling strategies of a virtual power plant aggregating a CSP plant and some responsive loads are presented using information gap decision theory (IGDT) to tackle multiple NSUs.

The bidding and offering strategies of hybrid power plants and load aggregators have been widely studied in the literature. For example, in [15], a multi-objective optimization model is presented and formulated as a three-stage SP for determining the optimal offering strategy of a
wind-thermal-energy storage generation company in the joint energy and reserve markets. In [16], the scheduling strategy for an electric vehicle aggregator in the energy market is addressed, in which the uncertain market prices are modeled by RO. In [17], a bi-objective stochastic model is presented for determining the optimal bidding strategy of a wind-thermal-photovoltaic system, and a hybrid weighted sum fuzzy approach is proposed to solve the bi-objective model and attain the Pareto solutions. When determining the optimal scheduling strategies, uncertainties such as the thermal production, wind power and market prices should be considered. Ignoring these uncertainties may significantly impact the obtained scheduling strategies and the revenues of the decision maker. Generally, the uncertainties can be categorized as two types, i.e., the non-stochastic uncertainties (NSUs), such as the thermal production and wind power that can be modeled within a certain set only due to the lack of their distribution information; and the stochastic uncertainties (SUs), such as market prices that can be described using a set of probability distributions or scenarios [7], [8].

With regard to the uncertainty management, SP [11], [15] RO [16], and IGDT [14] have been widely utilized in the literature, and are shown to be very effective and efficient in dealing with one specific type of uncertainties, i.e., SP is developed for SUs, while RO and IGDT are designed for NSUs [18], [19]. However, when there are coexistent NSUs and SUs in the problem, the use of one single technique would be less effective and may not be applicable [20]. Thus, hybrid methods that integrate two or more techniques are developed to solve the specific problem with coexistent uncertainties. For example, a hybrid stochastic robust approach (SRA) that integrates SP and RO [7], [8] and a chance-constrained information gap decision model (CCIGDM) that integrates chance constrained programming with IGDT [20] are developed for problems with the coexistent SUs and NSUs.

On the other hand, the risk attitude of the decision maker also affects the scheduling strategies and revenues. For example, a risk-averse (RA) decision maker prefers a conservative strategy to a risky one wishing to be immune to unfavorable uncertainties, whereas a risk-seeking (RS) decision maker prefers an opportunistic strategy to a conservative one by taking uncertainties as opportunity [19], [21]. In that regard, IGDT and the mixed conditional value at risk (CVaR) based SP are shown to be very effective to manage the performance risk of an optimization problem caused by uncertainties according to the risk attitude of the decision maker. Based on the prescribed robust and opportunistic models, IGDT can make optimal decisions for the RA and RS decision makers against severe NSUs, respectively, while showing how large the information gap is for a given performance level [19]. IGDT has been applied to many power system problems, such as microgrid planning [20], scheduling of virtual power plants [14], GenCos [22] as well as demand response aggregators [23], bidding and offering optimizations [24], [25]. CVaR is a risk measure for dealing with SUs, which is derived from the financial field and is widely used to trade off the expected revenue against the risk of possible losses caused by SUs for a given confidence level [18]. The conventional CVaR is generally utilized as a RA measure to avoid losses of a portfolio against unfavorable uncertainties [26]. Thus the mixed CVaR was developed for tackling SUs in a portfolio and hedging the revenue risk of the portfolio for not only the RA but also the RS decision makers [21].

In this work, based on our previous research on IGDT [14], a hybrid stochastic information gap approach (SIGA) is proposed in order to deal with the non-stochastic thermal production of the CSP plant and the stochastic market prices in the offering problem of the CSP plant. The proposed SIGA integrates the well-established IGDT with the mixed CVaR based SP, and is comprised of a robust stochastic information gap model (SIGM) and an opportunistic SIGM on the basic of the IGDT paradigm [19] for making decisions for the RA and RS CSP plants, respectively. Note that although the developed SIGA is used for addressing the offering strategy of a CSP plant, it can be applied to deal with intrinsically coexistent NSUs and SUs of any problem. Based on the developed SIGMs, it can take the risk attitude, i.e., RA or RS, of the decision maker into account and make not only the robust decision but also the opportunistic one. Compared with IGDT, the proposed SIGA is less conservative by appropriate management of NSUs and SUs. Compared with the hybrid SRA and CCIGDM [7], [8], [20], it is more robust against variations of uncertainties by introducing the risk hedge into the management of SUs via the mixed CVaR. On the other hand, by virtue of the advantages of IGDT and the mixed CVaR, the proposed SIGA can guarantee, or achieve, a desired performance level for the decision maker by showing how large the information gap of NSUs should be and at what confidence level the tradeoff between the expected revenue and the possible revenue loss caused by SUs is.

In summary, the main contributions of this work are:

1) the coexistent NSUs and SUs, as well as the risk attitude of the decision maker are well addressed and integrated together for the first time so as to build the optimal offering strategies of a price-taker CSP plant in the electricity markets;
2) a hybrid SIGA integrating the well-established IGDT with the mixed CVaR is proposed, by which the robust and opportunistic decisions can be attained to hedge the revenue risks against coexistent NSUs and SUs more effectively;
3) by using the SIGA, more revenues are achieved for the CSP plant through the better management of uncertainties, and the information gap of NSUs as well as the confidence level of the revenue tradeoff caused by SUs can be shown clearly.

II. OFFERING ARCHITECTURE AND DETERMINISTIC MODELS
A. STRATEGIC OFFERING ARCHITECTURE OF THE CSP PLANT
A price-taker CSP plant can participate in the DA and real-time (RT) markets by strategic energy offering. In the DA
market, the CSP plant should submit in advance its hourly offering quantity in the next day to the market operator. Once known the cleared quantity and price of the DA market, the CSP plant participates in the RT market by submitting the optimal offering quantity an hour prior to the operating hour based on the latest information, such as predictions of the thermal production of the CSP plant and RT market prices. A two-stage architecture is used for the CSP plant deriving its offering strategies in the DA and RT markets, in which the SIGA is implemented in both stages to manage the NSUs and SUs based on the risk attitude of the CSP plant. The two-stage offering architecture and the uncertainty management for building the optimal offering strategies are illustrated in Fig. 1.

As shown in Fig. 1, the CSP plant can make robust, or opportunistic, decisions strategically against the non-stochastic thermal production and stochastic market prices by using the robust SIGM, or the opportunistic SIGM, of the SIGA. In the first-stage, the DA offering strategy is decided. Since the CSP plant can participate in the RT market, the DA offering strategy determined in the first-stage may impact the RT one to be determined in the second-stage. Thus, it is necessary for the CSP plant to decide the DA offering strategy with the RT one considered. However, the RT offering strategy determined in the first-stage is not actually carried out in the RT market. After the DA market is cleared, the RT offering strategy in each hour of the operating day is decided in the second-stage using a rolling horizon manner.

In the next subsection, the deterministic offering models are presented based on the two-stage architecture.

### B. TWO-STAGE DETERMINISTIC MODELS FOR THE CSP PLANT

1) **FIRST-STAGE: DA OFFERING STRATEGY OPTIMIZATION**

In the first-stage, the CSP plant decides the DA offering strategy considering the RT one. The objective is to maximize the overall DA and RT revenues, which is represented as:

$$\max f_1(x) = \sum_{h \in T} \left( \lambda_h^{\text{DA}} P_h^{\text{DA}} + \lambda_h^{\text{RT}} P_h^{\text{RT}} - c_v e P_h^e \right).$$  (1)
The constraints for the first-stage model are as follows.\
\[ p_{\text{min}} \leq p_h^T \leq p_{\text{max}} \quad h \in T \]  \hspace{1cm} (2)\
\[ p_{h+1}^{\text{up}} - p_h^{\text{down}} \leq p_{\text{max}} \quad h \in T \]  \hspace{1cm} (3)\
\[ p_{h}^T = \eta_e p_h^T \quad h \in T \]  \hspace{1cm} (4)\
\[ p_h^T = \bar{P}_h^T - P_h^{\text{up}} + P_h^{\text{down}} - \sum_{t=0}^{T-1} p_{t+1}^{\text{on}} \quad h \in T \]  \hspace{1cm} (5)\
\[ v_h - v_{h-1} = u_h^{\text{on}} - u_h^{\text{off}} \quad h \in T \]  \hspace{1cm} (6)\
\[ u_h^{\text{on}} + u_h^{\text{off}} \leq 1 \quad h \in T \]  \hspace{1cm} (7)\
\[ \sum_{t=0}^{T-1} (1 - v_{h+t}) \geq u_h^{\text{off}} T^{\text{off}} \quad h \in T \]  \hspace{1cm} (8)\
\[ Q^\text{min} \leq Q_h^T \leq Q_{\text{max}} \quad h \in T \]  \hspace{1cm} (9)\
\[ Q_{h+1} = Q_h^T \left(1 - r\right) + \eta_e P_h^T - P_h^{\text{dc}} \quad h \in T \]  \hspace{1cm} (10)\
\[ 0 \leq P_h^{\text{dc}} \leq P_{h+1}^{\text{max}} / \eta_e \quad h \in T \]  \hspace{1cm} (11)\
\[ 0 \leq P_h^{\text{on}} \leq t_1^{\text{on}} P_{h+1}^{\text{max}} \quad h \in T \]  \hspace{1cm} (12)\
\[ I_{h+1}^\text{dc} + I_{h+1}^\text{ch} \leq 1 \quad h \in T \]  \hspace{1cm} (13)\
\[ Q_{T-1} = Q_{T-1}^{\text{final}} \]  \hspace{1cm} (14)\
\[ I_{h}^\text{dc} \leq v_h \quad h \in T \]  \hspace{1cm} (15)\
\[ P_h^{\text{DA}} + P_h^{\text{RT}} - P_h^{\text{sp}} = 0 \quad h \in T \]  \hspace{1cm} (16)\
\[ P_h^{\text{sup}} = u_h^{\text{on}} P_{\text{sp}} \quad h \in T \]  \hspace{1cm} (17)\

Equation (2) limits the electric power output of the CSP plant, or power block. Equation (3) represents the ramping up and down constraints. The electric power output is restricted by the thermal-electric efficiency and the thermal power input, as in (4). Equation (5) represents the power balance constraint of the CSP plant. Equations (6) and (7) represent the startup and shutdown constraints of power block. Equations (8) and (9) constrain the minimum offline and online times of power block, respectively. The energy and power constraints of thermal energy storage (TES) are shown in (10)-(15). The stored thermal energy of TES should be within a range, as in (10). The energy balance constraint for TES is shown in (11). The discharging and charging power of TES is constrained by (12) and (13), respectively. TES cannot charge or discharge at the same time, as in (14). The stored thermal energy of TES at the end of the operating day is constrained by (15). Power block must be in operation if TES is discharging, as in (16). The offering quantity of the CSP plant is constrained by (17). The startup power of power block is constrained by (18).

2) SECOND-STAGE: RT OFFERING STRATEGY OPTIMIZATION

Once the DA market is cleared, the CSP plant also has the opportunity to offer in the RT market, which is decided in the second-stage. In order to mitigate the prediction errors and consider the latest predictions and future possible conditions, the CSP plant in the RT market determines the offering strategy in a rolling horizon manner, also known as model predictive control [27], [28], i.e., in each operating hour \( h \) the second-stage model is optimized with a looking ahead horizon \( |T|-h+1 \) based on the updated latest information by hour \( h-1 \), but only the offering strategy in operating hour \( h \) is actually implemented; then in \( h+1 \) the second-stage model is solved again with a looking ahead horizon \( |T|-h \) and only the offering strategy in \( h+1 \) is implemented [29].

By denoting \( y_h = y_{[h:T]} \), the offering strategy optimization model in the RT market at hour \( h \) can be expressed as follows.

\[ \max f_h(y_h) \mid \{x^{DA}_{h-1}, y_{h-1} \} = \sum_{t\geq h} \beta_{t}^{RT} (P_{t}^{RT} - c_{t}^{RT} P_{t}^{RT}) \]  \hspace{1cm} (19)

\[ \text{s.t. : Equations (2)-(18)} \]  \hspace{1cm} (20)

Thus far, accurate predictions for the thermal production of the CSP plant and the DA and RT market prices are assumed in both the first-stage and second-stage deterministic models, which can be deemed as with the risk-neutral (RN) attitude. However, the fluctuation and variability nature of the NSUs and SUs may pose revenue risk to the CSP plant, and the risk attitude, i.e., RA or RS, of the decision maker also impacts the offering strategy and revenue. In the next section, the SIGA integrating IGDT with the mixed CVaR is proposed to handle uncertainties and the robust and opportunistic SIGMs are presented for the RA and RS CSP plants, respectively.

III. THE SIGA FOR STRATEGIC OFFERING OF THE CSP PLANT

In order to facilitate the formulation of the SIGA, the following compact matrix form is utilized for the two-stage architecture. Since any equation can be denoted as two inequations, i.e., \( "a = b" \) is equivalent to \( "a \geq b" \) and \( "a \leq b" \), the matrix form for the two-stage offering problems is as follows.

\[ \max f_m(z_m, \mu_m, \gamma_m) = c_m^T z_m + \lambda_m^T v_m \]  \hspace{1cm} (21)

\[ \text{s.t. : } A_m z_m + B_m v_m \geq 0 \]  \hspace{1cm} (22)
\[ C_m \mu_m + D_m \bar{u}_m \geq 0 \]  \hspace{1cm} (23)
\[ W_m v_m \geq b_m \]  \hspace{1cm} (24)
\[ T_m \phi_m \geq 0 \]  \hspace{1cm} (25)
\[ H_m v_m + G_m \phi_m \geq 0 \]  \hspace{1cm} (26)

where \( m \in \{I, II\} \) denotes which stage the matrix form represents. \( z_1 = x \) and \( z_2 = y \). Note that the optimization horizon of the matrix form should change according to the value of \( m \). \( v_m \) is a vector of power and energy related variables, such as \( P_{h}^T, P_{h}^{\text{sup}}, P_{h}^{\text{sp}}, \) and \( Q_h \). \( b_m \) is a vector of power and energy related parameters, such as \( \beta^{RT} \) and \( \mu^{RT} \). \( \lambda_m^T \) and \( \gamma_m^T \) represent coefficient matrices. Constraints (22) and (23) correspond to (17) and (5), respectively. Constraint (24) represents (3), (4), (10) and (15). Constraint (25) represents (6)-(9), (14) and (16). Constraint (26) represents (2), (5), (11)-(13) and (18).

A. IGDT FOR MANAGEMENT OF NSUs

The offering strategies of the CSP plant are associated with the NSUs and SUs. The thermal production of the CSP plant is deemed as the NSU [7], [8], which is tackled using IGDT.
The widely-used fractional uncertainty model of IGDT is utilized in this work to represent the info gap region that restricts the predicted and actual thermal production, as denoted by:

$$U_m(\alpha, \bar{u}_m) = \{u_m : |u_m - \bar{u}_m| \leq \alpha \bar{u}_m, \alpha \geq 0\}, \quad \forall m \in \{I, II\}$$  \hspace{1cm} (27)

where $\alpha$ represents the uncertainty horizon of the thermal production, whereas the lower-level one (30)-(40) maximizes the RS CSP plant’s revenue based on the info gap region defined by $\alpha$. The two models are connected by an user-set opportunistic revenue threshold, as in (38). By using the opportunistic IGDT, the RS CSP plant strives to achieve more revenues, if the actual thermal production is favorable enough and beyond the info gap region defined by the optimized uncertainty horizon. Less revenue than the threshold is acceptable, while larger revenue is possibly achieved only under favorable thermal production. Since $\alpha$ can be regarded as a constant in the lower-level, it is easy to conclude that the maximum of the opportunistic model can be attained only at the upper bound of the info gap region, i.e., the CSP plant with the highest thermal production. As a result, the bi-level model can be simplified as the following single level one.

$$\delta_m(z_m, u_m, \alpha_m) = \max \frac{m}{\bar{z}_m} \alpha_m \hspace{1cm} (41)$$

The upper-level model (28)-(30) maximizes the uncertainty horizon $\alpha$ of the thermal production, whereas the lower-level one (30)-(32) minimizes the RA CSP plant’s revenue under the info gap region defined by $\alpha$. The two models are connected by an user-set robust revenue threshold, as in (29). By using the robust IGDT, the revenue of the RA CSP plant under NSUs from the thermal production would not be less than the robust revenue threshold if the actual thermal production falls into the info gap region defined by (27). In the lower-level model, $\alpha$ can be regarded as a constant. So this model is actually a linear programming problem, and the minimum can be attained only at the bound of the info gap region. Since less thermal production will surely lead to less offering quantity and revenue, the solution of the lower-level model can be attained only at the lower bound of the info gap region. As a result, the bi-level model can be simplified as a single level one, i.e.

$$\kappa_m(z_m, u_m, \varepsilon_m) = \max \frac{m}{z_m} \alpha_m \hspace{1cm} (33)$$

$$s.t.: f_m^{RA} \geq f_m^{RA0} = f_m^{R0}(1 - \varepsilon_m) \hspace{1cm} (34)$$

$$f_m^{RA} = \min_{u_m \in U_m(a_m)} f_m(z_m, u_m, \bar{c}_m) \hspace{1cm} (35)$$

$$s.t.: \ C_m v_m + D_m u_m \geq 0 \hspace{1cm} (36)$$

Equations (22), (24) – (26) and (31). 

The opportunistic IGDT for optimizing the DA and RT offering strategies of the RS CSP plant, i.e., RS offering strategies, can be represented as the following bi-level model.

$$\delta_m(z_m, u_m, \alpha_m) = \min \frac{m}{\bar{z}_m} \alpha_m \hspace{1cm} (37)$$

$$s.t.: f_m^{RS} \geq f_m^{RS0} = f_m^{R0}(1 + \alpha_m) \hspace{1cm} (38)$$

$$f_m^{RS} = \max_{u_m \in U_m(a_m)} f_m(z_m, u_m, \bar{c}_m) \hspace{1cm} (39)$$

$$s.t.: \ C_m v_m + D_m u_m \geq 0 \hspace{1cm} (40)$$

The upper-level model (37)-(39) minimizes the uncertainty horizon $\alpha$ of the thermal production, whereas the lower-level one (39)-(40) maximizes the RS CSP plant’s revenue based on the info gap region defined by $\alpha$. The two models are connected by an user-set opportunistic revenue threshold, as in (38). By using the opportunistic IGDT, the RS CSP plant strives to achieve more revenues, if the actual thermal production is favorable enough and beyond the info gap region defined by the optimized uncertainty horizon. Less revenue than the threshold is acceptable, while larger revenue is possibly achieved only under favorable thermal production. Since $\alpha$ can be regarded as a constant in the lower-level, it is easy to conclude that the maximum of the opportunistic model can be attained only at the upper bound of the info gap region, i.e., the CSP plant with the highest thermal production. As a result, the bi-level model can be simplified as the following single level one.

$$\delta_m(z_m, u_m, \alpha_m) = \min \frac{m}{\bar{z}_m} \alpha_m \hspace{1cm} (41)$$

The SUs in the offering problem are also of significance, posing revenue risks if not tackled appropriately. Market prices are the main sources of SUs [7], [8], which are associated with the objective function $f_m(\cdot)$ only, where $m \in \{I, II\}$. Denote the stochastic variable as $\xi$, then the offering model with SUs can be represented as

$$f_m[z_m, \bar{u}_m, \alpha_m(\xi)] = c_m^T(\xi)x + \lambda_m^Tv_m, \quad \forall m \in \{I, II\} \hspace{1cm} (45)$$

As mentioned before, SP is applied to manage SUs from market prices. Among the SP applications, CVaR is one of the most significant risk hedging methods [18], [21], [30]. Denote $F_{z_m}$ as the distribution function of $f_m(\cdot)$. Then the conventional CVaR for a given quantile $\theta \in (0, 1]$ can be expressed as:

$$\text{CVaR}^{\text{con}}_{\theta, m} [z_m, \alpha_m(\xi)] = \mathbb{E} \left[ f_m[z_m, \bar{u}_m, \alpha_m(\xi)] \mid f_m[z_m, \bar{u}_m, \alpha_m(\xi)] \leq F_{z_m}^{-1}(\theta) \right] \hspace{1cm} (46)$$

where $\text{CVaR}^{\text{con}}_{\theta, m}$ represents the expected offering revenue given revenue is below $F_{z_m}^{-1}(\theta)$. Since the conventional CVaR is generally used as a RA measure and may not be utilized for the RS CSP plant who prefers stochastic variable and makes ambitious decisions under SUs, the mixed CVaR is introduced to manage stochastic market prices and attain offering strategies for not only the RA but also the RS CSP plants.

Based on the Hurwicz’s criterion [31], which selects, in order to find a tradeoff between the extremes led to by the pessimist and optimist criteria, a combination of the minimum and maximum revenues of each given offering
decision $z_m$, the mixed CVaR for the offering problem can be represented as

$$CVA_{m,\theta}^{\text{mix}} = \pi \mathbb{E} \left[ f_m[z_m, \bar{u}_m, c_m(\xi)] \right] + \frac{(1 - \pi)}{\pi} \mathbb{E} \left[ f_m[z_m, \bar{u}_m, c_m(\xi)] \right] \geq F_{z_m}^{-1}(\theta)$$

(47)

where $\pi \in [0, 1]$ is named as pessimism coefficient [31]. The mixed CVaR (47) considers not only the expected offering revenue below but also that above $F_{z_m}^{-1}(\theta)$, thus it is a comprehensive risk measure compared with the conventional CVaR and can be used to make offering decisions considering the risk attitude [21], [30]. Equation (47) is equivalent to

$$CVA_{m,\theta}^{\text{mix}} = \frac{\pi - \theta}{1 - \theta} CVA_{m,\theta}^{\text{con}} + \frac{1 - \pi}{1 - \theta} \mathbb{E} \left[ f_m[z_m, \bar{u}_m, c_m(\xi)] \right]$$

(48)

which can be further simplified as:

$$CVA_{m,\theta}^{\text{mix}} = \mathbb{E} \left[ f_m[z_m, \bar{u}_m, c_m(\xi)] \right] + \beta CVA_{m,\theta}^{\text{con}}$$

(49)

where $\beta = (\pi - \theta)/(1 - \pi)$, $\beta \in (-1, +\infty)$. Generally, for the decision making under SUs, a RA decision maker prefers the expected value of the stochastic variable to the stochastic variable itself. So a RA CSP plant would prefer $\mathbb{E}[-]$ to the stochastic revenue $f_m[\cdot]$ for all offering strategies $z_m$. On the other hand, a RN CSP plant is indifferent to the stochastic variable, and a RS one prefers $f_m[\cdot]$. For the mixed CVaR (49), the risk attitude of the CSP plant is determined by the following criteria: i) RA if $\beta > 0$, or $\theta < \pi$; ii) RN if $\beta = 0$, or $\theta = \pi$; iii) RS if $\beta < 0$, or $\theta > \pi$ [21]. With the risk attitude of the CSP plant considered, the mixed CVaR can be used as a substitution for the objective of the offering strategy optimization model under SUs.

In essence, the mixed CVaR (49) for the strategic offering problem is a stochastic optimization model, so the scenario based solving methods for SP can be used to solve the mixed CVaR. The scenarios generation and reduction techniques can be found in [18], and are not the focuses of this work.

C. MIXED CVAR BASED SIGA FOR STRATEGIC OFFERING

1) ROBUST SIGM FOR RA OFFERING

Based on IGDT and the mixed CVaR, the robust SIGM of the SIGA for the RA CSP plant can be formulated as:

$$\kappa_m(z_m, u_m, \epsilon_m) = \max_{z_m} \alpha$$

s.t. : $CVA_{m,\theta}^{\text{mix}} \geq \frac{f_m^R(1 - \epsilon_m)}{1 + \epsilon_m} = f_m^R(1 - \epsilon_m)$$

(50)

$$CVA_{m,\theta}^{\text{mix}} = \sum_s \gamma_m f_{m,s} \left( z_m, u_m, c_{m,s} \right) + \beta$$

$$\times \left\{ f_m^0 - \frac{1}{\theta} \sum_s \gamma_m \left[ f_m^0 - f_{m,s} \left( z_m, u_m, c_{m,s} \right) \right]^+ \right\}$$

(51)

(52)

$$\beta > 0$$

(53)

Equations (22), (24) – (26), (31), and (35). (54)

2) OPPORTUNISTIC SIGM FOR RS OFFERING

Similarly, the opportunistic SIGM of the SIGA for the RS CSP plant can be represented as:

$$\delta_m(z_m, u_m, \epsilon_m) = \min_{z_m} \alpha$$

s.t. : $CVA_{m,\theta}^{\text{mix}} \geq f_m^{R(1 + \epsilon_m)} = f_m^R$$

(56)

$$\beta < 0$$

(57)

Equations (22), (24) – (26), (31), (43), (52) and (55). (59)

IV. CASE STUDY

A CSP plant with 100 MW-e rated electric power output is used to demonstrate the offering strategies. Parameters of the CSP plant, the solar radiance and thermal production are based on the System Advisor Model (SAM) [32]. The solar multiple, i.e., the ratio between the rated output of solar field and the rated input of power block, is set as 2.5. The charging/discharging efficiency of TES is 98.5%. TES has with ten hours full load energy capacity. The required startup energy of the CSP plant is 40 MW-t-h. The hourly thermal loss factor of TES is 0.035%. The required thermal energy of TES at the end of the day is forty percent of its energy capacity. The minimum online time and minimum offline time of power block are two and one hours, respectively. DA and RT market prices are obtained from PJM market. The auto regressive integrated moving average (ARIMA) method is used to predict market prices [33] and the thermal production [34]. Generally, the quantile $\theta$ takes values 97.5%, 95% or 90% in power system decision making problems and financial fields. In this work, it is set as 90% for the mixed CVaR. The SIGMs are solved by the SBB solver in general algebraic modeling system (GAMS).

A. ROBUST SIGM FOR RA OFFERING

Firstly, the NSUN model (55) with perfect predictions of non-stochastic thermal production is solved. Set $\beta = 1$ for
demonstration. In the first-stage, mixed CVaR $f^{R0}_I$ is optimized as $220870$, while the expected revenue, i.e., the first term in (55), from the DA and RT markets is optimized as $110618$ and the conventional CVaR, i.e., the second term in (55), given $f^{0}_I = 113916$, is optimized as $110252$ with a confidence level $\theta = 90\%$. The results of the NSUN model in the second-stage, which is solved in a rolling horizon manner, in each operating hour are shown in Table 1, where “mcVaR” and “Ex.Rev.” represent the values of the mixed CVaR and expected revenue, respectively. Note that in the first-stage the variables and decisions for the DA offering problem consider those for the RT market, while in the second-stage the variables and decisions for the RT offering problem in each operating hour $h$ consider those for the subsequent RT market participation in the looking ahead horizon $[T]-h$.

| TABLE 1. Mixed CVaR and expected revenue of the NSUN model (Unit: $). |
|-----------------|-----------------|-----------------|-----------------|
| $h$             | mcVaR           | Ex.Rev.         | $h$             | mcVaR           | Ex.Rev.         |
| 1               | 41173           | 26645           | 9               | 34428           | 17280           | 17               | 4489             | 2250             |
| 2               | 40808           | 26465           | 10              | 33874           | 17007           | 18               | 0                | 0                |
| 3               | 39018           | 19575           | 11              | 35025           | 17548           | 19               | 0                | 0                |
| 4               | 36807           | 18429           | 12              | 33821           | 16938           | 20               | 0                | 0                |
| 5               | 35714           | 17888           | 13              | 33689           | 16885           | 21               | 0                | 0                |
| 6               | 35061           | 17580           | 14              | 33939           | 17019           | 22               | 0                | 0                |
| 7               | 33395           | 16729           | 15              | 18388           | 9227            | 23               | 0                | 0                |
| 8               | 35112           | 17585           | 16              | 18382           | 9219            | 24               | 0                | 0                |

Then, the robust SIGM (50)-(54) is optimized to attain the RA offering strategies. The robust revenue threshold factor $\varepsilon_m$, where $m \in \{I, II\}$, is set as 20%. Figs. 2 and 3 show the robust info gap regions attained from uncertainty horizon $\kappa_m$ based on (27), and the RA offering scheme in the DA and RT markets.

| FIGURE 2. Optimized robust info gap region. |

For the DA strategic offering in the first-stage, the uncertainty horizon $\kappa_I$ is optimized as 0.201. That is, if the variation of uncertain thermal production is not more than 20.1% of the predicted value, the mixed CVaR $\text{CVaR}_{mix}^{R}$ is at least $f^{R0}_{I} = 220870(1-\varepsilon_I) = 176696$, while the expected revenue from the DA and RT markets, i.e., the first term in (52), is at least $89682$. However, by considering the stochastic market prices, the value of conventional CVaR, i.e., the second term in (52), given $f^{0}_I = 92760$, is $87014$ with a confidence level 90%. In other words, for the given non-stochastic thermal production whose uncertainty horizon is no greater than 0.201 and stochastic market prices, the RA CSP plant can achieve an expected revenue $89682$, and it can guarantee, at a confidence level 90%, a revenue $87014$.

For the RT strategic offering in the second-stage, the robust SIGM is solved in a rolling horizon manner for each operating hour. The average uncertainty horizon is 0.0295. Table 2 shows the optimized mixed CVaR and expected revenue in each hour. Take hour 6 as an example for demonstrating the robust SIGM. In hour 6, $\kappa_{II}$ is optimized as 0.0421. In other words, if the variation of uncertain thermal production is not more than 4.21% of the predicted value, the RA CSP plant can achieve, given the stochastic RT market price, an expected revenue $14068$ in the RT market, and it can guarantee, at a confidence level 90%, a revenue $13981$.

| TABLE 2. Mixed CVaR and expected revenue of the robust SIGM (Unit: $). |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| $h$             | mcVaR           | Ex.Rev.         | $h$             | mcVaR           | Ex.Rev.         | $h$             | mcVaR           | Ex.Rev.         |
| 1               | 32939           | 16534           | 9               | 27542           | 13821           | 17               | 3591            | 1801            |
| 2               | 32647           | 16396           | 10              | 27099           | 13629           | 18               | 0               | 0               |
| 3               | 31214           | 15659           | 11              | 28020           | 14052           | 19               | 0               | 0               |
| 4               | 29446           | 14758           | 12              | 27057           | 13561           | 20               | 0               | 0               |
| 5               | 28571           | 14326           | 13              | 26931           | 13519           | 21               | 0               | 0               |
| 6               | 28049           | 14068           | 14              | 27151           | 13616           | 22               | 0               | 0               |
| 7               | 26716           | 13397           | 15              | 14710           | 7378            | 23               | 0               | 0               |
| 8               | 28090           | 14081           | 16              | 14706           | 7377            | 24               | 0               | 0               |

**B. OPPORTUNISTIC SIGM FOR RS OFFERING**

Firstly, the NSUN model (55) for the opportunistic SIGM (56)-(59) can be solved. Set $\beta$ as -0.5 for demonstration. $f^{R0}_{I}$ is optimized as $55536$, while the expected revenue and the conventional CVaR (given $f^{1}_I = 113916$) are optimized as $110646$ and $110220$ respectively. Table 3 shows the optimized results of the NSUN model in the second-stage.
Then, the opportunistic SIGM (56)-(59) can be optimized to attain the RS offering strategies. The opportunistic revenue threshold factor $\zeta_m$, where $m \in \{I, II\}$, is set as 20%. The optimized results of the opportunistic info gap regions and RS offering schemes are shown in Figs. 4 and 5, respectively.

In the first-stage, the uncertainty horizon $\delta_I$ is optimized as 0.360. That is, if the variation of uncertain thermal production is not less than 36.0% of the predicted value, the mixed CVaR $\text{CVaR}^{\text{mix}}_{I, 90\%}$ can be no less than $f^{\text{RS0}}_I = \$55536(1 + \zeta_I) = \$66643$, while the expected revenue from the DA and RT markets is at least $124656$. However, by considering the stochastic market prices, the value of conventional CVaR, given $f^0_I = \$126872$, is $\$116026$ with 90% confidence level. In other words, if the uncertainty horizon of the thermal production is not less than 36.0% of the predicted value, the RS CSP plant may attain, given stochastic market prices, an expected revenue $\$124656$, or, at 90% confidence level, a revenue $\$116026$ in the DA and RT markets.

In the second-stage, the average of the optimized uncertainty horizon is 0.0312. Table 4 shows the optimized mixed CVaR and expected revenue in each hour. Take hour 14 as an example. In hour 14, $\delta_{II}$ is optimized as 0.0457. In other words, if the variation of uncertain thermal production is not less than 4.57% of the predicted value, the RS CSP plant may achieve, given the stochastic RT market price, an expected revenue $\$19431$ or, at 90% confidence level, a revenue $\$18325$ in the RT market.

### TABLE 3. Mixed CVaR and expected revenue of the NSUN model (Unit: $).

| $h$ | mCVaR | Ex.Rev. | $h$ | mCVaR | Ex.Rev. | $h$ | mCVaR | Ex.Rev. |
|-----|-------|---------|-----|-------|---------|-----|-------|---------|
| 1   | 10379 | 20645   | 9   | 8704  | 17280   | 17  | 1129  | 2250    |
| 2   | 10291 | 20465   | 10  | 8571  | 17007   | 18  | 0     | 0       |
| 3   | 9852  | 19574   | 11  | 8809  | 17548   | 19  | 0     | 0       |
| 4   | 9238  | 18429   | 12  | 8496  | 16913   | 20  | 0     | 0       |
| 5   | 8974  | 17888   | 13  | 8484  | 16885   | 21  | 0     | 0       |
| 6   | 8849  | 17586   | 14  | 8557  | 17019   | 22  | 0     | 0       |
| 7   | 8395  | 16729   | 15  | 4646  | 9227    | 23  | 0     | 0       |
| 8   | 8821  | 17585   | 16  | 4636  | 9219    | 24  | 0     | 0       |

### TABLE 4. Mixed CVaR and expected revenue of the opportunistic SIGM (Unit: $).

| $h$ | mCVaR | Ex.Rev. | $h$ | mCVaR | Ex.Rev. | $h$ | mCVaR | Ex.Rev. |
|-----|-------|---------|-----|-------|---------|-----|-------|---------|
| 1   | 12454 | 23240   | 9   | 10445 | 19917   | 17  | 1355  | 6110    |
| 2   | 12349 | 23074   | 10  | 10285 | 19825   | 18  | 0     | 0       |
| 3   | 11822 | 22145   | 11  | 10671 | 20683   | 19  | 0     | 0       |
| 4   | 11086 | 20779   | 12  | 10195 | 19336   | 20  | 0     | 0       |
| 5   | 10786 | 20551   | 13  | 10180 | 19296   | 21  | 0     | 0       |
| 6   | 10619 | 20066   | 14  | 10268 | 19431   | 22  | 0     | 0       |
| 7   | 10074 | 19153   | 15  | 5575  | 11713   | 23  | 0     | 0       |
| 8   | 10585 | 20048   | 16  | 5563  | 11654   | 24  | 0     | 0       |

### C. SENSITIVITY ANALYSES ON UNCERTAINTY HORIZON AND $\beta$

In order to investigate the impacts of uncertainty horizon and coefficient $\beta$ on the expected revenue of the CSP plant, the robust and opportunistic SIGMs are optimized for the first-stage DA strategic offering problem using various parameters since the analyses and conclusions are the same for the second-stage RT strategic offering problem. Figs. 6 and 7 show the sensitivity analysis results of the robust and opportunistic SIGMs, respectively.
As seen from Fig. 6, the expected revenue of the RA CSP plant decreases with the increase of $\beta$. On the other hand, the expected revenue also decreases as the uncertain horizon rises. In other words, the larger the coefficient $\beta$ and/or uncertainty horizon, the less expected revenue the RA CSP plant can attain. Since the larger $\beta$ and/or uncertainty horizon are, the more conservative to SUs and/or NSUs the CSP plant is, this conclusion is consistent with the decision preference of the RA CSP plant, who makes robust offering decision wishing to achieve an expected revenue against pernicious SUs and/or NSUs.

In Fig. 7, for $\beta = -0.5 \sim -0.1$, there is only one feasible pair of $\delta_I$ and the expected revenue. This is because the capacity of the CSP plant is not large enough that it cannot accommodate more thermal production. However, for $\beta = -0.9 \sim -0.6$, as $\beta$ rises, the expected revenue of the RS CSP plant increases. On the other hand, the expected revenue also increases as the uncertain horizon rises. In other words, the larger $\beta$ and/or uncertainty horizon are, the more expected revenue the RS CSP plant can attain. Since larger $\beta$ and/or uncertainty horizon mean that the CSP plant is more adventurous to SUs and/or NSUs, this conclusion accords with the decision preference of the RS CSP plant, who makes opportunistic offering decision wishing to achieve more expected revenue by utilizing propitious SUs and/or NSUs.

D. COMPARISONS AND AFTER-THE-FACT ANALYSES

Comparisons of the proposed SIGA with IGDT, SRA and CCIGDM are shown in Table 5 [7], [8], [18]–[21]. In Table 5, “NSU-SU” represents the coexistence of NSUs and SUs. It is clear that only the proposed SIGA can tackle coexistent NSUs and SUs for not only the RA but also the RS decision makers.

To further verify the effectiveness of the proposed SIGA, the actual revenues (determined by the actual thermal production and market prices) attained by different methods for the RA and RS CSP plants in the markets are compared. The simulation period is a week, from July 1st to 7th, 2018. The DA and RT market prices are based on the PJM market, and the thermal productions are obtained from the SAM. Both the mix CVaR of the proposed SIGA and the stochastic optimization in SRA are optimized using the scenario-based method. For each day, 5000 scenarios are generated based on the predicted market prices using the Monte Carlo approach, and 10 typical scenario are obtained finally using the transportation problem based scenario reduction technique [18]. The original 5000 scenarios are also used in CCIGDM, whose risk tolerance level is set as 0.1 [20]. The robust revenue threshold factors for the proposed robust SIGM, the robust IGDT and CCIGDM are set as 20%. Also, the opportunistic revenue threshold factors for both the proposed opportunistic SIGM and the opportunistic IGDT are set as 20%. Since IGDT can only tackle NSUs, the expectations on various market price scenarios are used as predictions. The range of NSUs in SRA is based on the info gap region optimized by the robust IGDT.

As seen from Table 6, for the RA CSP plant, the proposed robust SIGM can achieve more revenue in most of the days than the robust IGDT, as in days 1, 2, 4, 5, and 7. In days 3 and 6, the revenues of the robust SIGM are less than those of the robust IGDT. This is because the market prices in these days are substantially overestimated, i.e., too low to be captured by the scenarios. Since the SUs are handled using the mixed CVaR based SP instead of IGDT, the robust SIGM is less conservative than the robust IGDT. As a result, the robust SIGM achieves less revenue in these two days due to the low actual prices. The revenues attained by the robust SIGM and SRA are much more close to each other in days 1, 2, 4, 5, and 7, while the revenue attained by the former is slightly higher than the latter in days 3 and 6 (when market prices are significantly overestimated) thanks to the risk hedge by the mixed CVaR against SUs. It is also shown in Table 6 that although the revenues attained by the robust SIGM and CCIGDM are close to each other in days 2, 4 and 6, the revenues of the latter in days 1, 3 and 7 are less than that of the former. Note that CCIGDM uses chance constrained programming for dealing with SUs and the sampling strategy.
for chance constraints [20], which may introduce additional randomness in the sampling process. Thus it cannot guarantee an optimal set of scenarios and the attained solution of the problem may be worse than that attained by SP. The comparisons results in Table 6 demonstrate that the proposed robust SIGA can make optimal decisions for the RA decision maker against NSUs and SUs, which are less conservative than the robust IGDT but more robust than SRA and CCIGDM.

**TABLE 7.** Actual revenues of RS CSP plant using various methods (Unit: $).

| Day | Opportunistic SIGM | Opportunistic IGDT [22, 25] | SRA [7, 8] | CCIGDM [20] |
|-----|-------------------|-----------------------------|------------|-------------|
| 1   | 127720            | 122455                      | 85756      | 85967       |
| 2   | 71870             | 69937                       | 49705      | 49756       |
| 3   | 57869             | 55689                       | 39448      | 39512       |
| 4   | 65747             | 65649                       | 46996      | 46947       |
| 5   | 63937             | 60701                       | 44626      | 44944       |
| 6   | 65020             | 58970                       | 42053      | 42443       |
| 7   | 82515             | 81952                       | 57404      | 57025       |
| Total | 531998            | 515352                      | 366987     | 366606      |

As illustrated in Table 7, for the RS CSP plant, the opportunistic SIGM attains more revenue than the IGDT one in all of the seven days. It is also shown clearly that both the opportunistic SIGM and IGDT achieve more revenue than the methods developed for the RA decision maker, i.e., SRA and CCIGDM, by taking uncertainties as opportunities. The results show that by using the opportunistic SIGM, more information can be captured and the propitious uncertainty situations can be made the best for making favorable decisions.

The comparisons in Tables 6 and 7 demonstrate that the proposed SIGA is superior to the IGDT, SRA and CCIGDM by virtue of the appropriate management of NSUs and SUs thus it could be an effective tool for making decision in problems with coexistent NSUs and SUs as well as the risk preference.

**V. CONCLUSION**

In this work, the offering problem of a CSP plant in the DA and RT market is addressed. A SIGA integrating the well-established IGDT with the mixed CVaR based SP is proposed to handle NSUs and SUs considering the risk attitude of the CSP plant. The robust and opportunistic SIGMs are proposed for optimizing RA and RS offering strategies, respectively. Simulations demonstrate that the proposed SIGMs can make optimal offering decisions against uncertainties. The RA CSP plant can attain, at a certain confidence level, an expected revenue against pernicious NSUs and SUs by using the robust SIGM, whereas the RS CSP plant may achieve, at a certain confidence level, an expected revenue under propitious NSUs and SUs by using the opportunistic SIGM. Comparisons with other methods for uncertainty management show that the SIGA can be an effective tool to manage risk against the coexistent NSUs and SUs.

The proposed SIGA can be used to deal with intrinsically coexistent NSUs and SUs of any problem, though it is applied for optimizing the offering strategies of a CSP plant. On the other hand, the integration of CSP plants with loads is of practical significance but is not considered in this work, thus future research may focus on the optimal offering strategy for integrating CSP plants with loads using the proposed SIGA.

**REFERENCES**

[1] R. Dominguez, A. J. Conejo, and M. Carrión, “Toward fully renewable electric energy systems,” *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 316–326, Jan. 2015.

[2] E. Du, N. Zhang, B. M. Hodge, Q. Wang, C. Kang, B. Kroposki, and Q. Xia, “The role of concentrating solar power towards high renewable energy penetrated power systems,” *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6630–6641, Nov. 2018.

[3] J. Usaoa, “Operation of concentrating solar power plants with storage in spot electricity markets,” *IET Renew. Power Gener.*, vol. 6, no. 1, pp. 59–66, 2012.

[4] Z. Wu, M. Zhou, J. Wang, E. Du, N. Zhang, and G. Li, “Profit-sharing mechanism for aggregation of wind farms and concentrating solar power,” *IEEE Trans. Sustain. Energy*, early access, Jan. 20, 2020, doi: 10.1109/TSTE.2020.2967860.

[5] R. Chen, H. Sun, Q. Guo, Z. Li, T. Deng, W. Wu, and B. Zhang, “Reducing generation uncertainty by integrating CSP with wind power: An adaptive robust optimization-based analysis,” *IEEE Trans. Sustain. Energy*, vol. 6, no. 2, pp. 583–594, Apr. 2015.

[6] H. Liu, R. Zhai, J. Fu, Y. Wang, and Y. Yang, “Optimization study of thermal-storage PV-CSP integrated system based on GA-PSO algorithm,” *Sol. Energy*, vol. 184, pp. 391–409, May 2019.

[7] R. Dominguez, L. Baringo, and A. J. Conejo, “Optimal offering strategy for a concentrating solar power plant,” *Appl. Energy*, vol. 98, pp. 316–325, Oct. 2012.

[8] G. He, Q. Chen, C. Kang, and Q. Xia, “Optimal offering strategy for concentrating solar power plants in joint energy, reserve and regulation markets,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1245–1254, Jul. 2016.

[9] M. J. Vasallo and J. M. Bravo, “A MPC approach for optimal generation scheduling in CSP plants,” *Appl. Energy*, vol. 165, pp. 357–370, Mar. 2016.

[10] E. G. Copoescu, J. M. Bravo, M. J. Vasallo, and D. M. Santos, “Optimal scheduling in concentrating solar power plants oriented to low generation cycling,” *Renew. Energy*, vol. 135, pp. 789–799, May 2019.

[11] D. Yu, A. G. Ebadi, K. Jermisittiparsert, H. N. Jabarullah, M. V. Vasilevja, and S. Nojavan, “Risk-constrained stochastic optimization of a concentrating solar power plant,” *IEEE Trans. Sustain. Energy*, early access, Jul. 10, 2019, doi: 10.1109/TSTE.2019.2927735.

[12] H. M. I. Pousinho, H. Silva, V. M. F. Mendes, M. Collares-Pereira, and C. Pereira Cabrita, “Self-scheduling for energy and spinning reserve of wind/CSP plants by a MILP approach,” *Energy*, vol. 78, pp. 524–534, Dec. 2014.

[13] H. M. I. Pousinho, J. Esteves, V. F. M. Mendes, C. C. Pereira-Cabrita, and C. Pereira Cabrita, “Bilevel approach to wind-CSP day-ahead scheduling with spinning reserve under controllable degree of trust,” *Renew. Energy*, vol. 85, pp. 917–927, Jan. 2016.

[14] Y. Zhao, Z. Lin, F. Wen, Y. Ding, J. Hou, and L. Yang, “Risk-constrained day-ahead scheduling for concentrating solar power plants with demand response using info-gap theory,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 10, pp. 5475–5488, Oct. 2019.

[15] H. Khaleie, A. Abdollahi, M. Shafie-khah, A. Anvari-Moghaddam, S. Nojavan, P. Siano, and J. P. S. Catalão, “Coordinated wind-thermal-energy storage offering strategy in energy and spinning reserve markets using a multi-stage model,” *Appl. Energy*, vol. 259, Feb. 2020, Art. no. 114168.

[16] S. Seyyedeh Barhagh, B. Mohammad-Ivaloo, A. Anvari-Moghaddam, and S. Asadi, “Risk-involved participation of electric vehicle aggregator in energy markets with robust decision-making approach,” *J. Cleaner Prod.*, vol. 239, Dec. 2019, Art. no. 118076.

[17] H. Khaleie, A. Abdollahi, M. Shafie-khah, P. Siano, S. Nojavan, A. Anvari-Moghaddam, and J. P. S. Catalão, “Co-optimized bidding strategy of an integrated wind-thermal-photovoltaic system in deregulated electricity market under uncertainties,” *J. Cleaner Prod.*, vol. 242, Jan. 2020, Art. no. 118434.

[18] G. C. Pflug and A. Pichler, *Multistage Stochastic Optimization*. New York, NY, USA: Springer-Verlag, 2014.
Y. Zhao et al.: Mixed CVaR-Based SIGA for Building Optimal Offering Strategies of a CSP Plant in Electricity Markets

[19] Y. Ben-Haim, Info-Gap Decision Theory: Decisions Under Severe Uncertainty, 2nd ed. San Diego, CA, USA: Academic, 2006.

[20] X. Cao, J. Wang, and B. Zeng, “A chance constrained information-gap decision model for multi-period microgrid planning,” IEEE Trans. Power Syst., vol. 33, no. 3, pp. 2684–2695, May 2018.

[21] W. Jammerneck and P. Kischka, “Risk-averse and risk-taking newsvendors: A conditional expected value approach,” Rev. Manage. Sci., vol. 1, no. 1, pp. 93–110, Apr. 2007.

[22] B. Mohammadi-Ivatloo, H. Zareipour, N. Amjady, and M. Ehsan, “Application of information-gap decision theory to risk-constrained self-scheduling of GenCos,” IEEE Trans. Power Syst., vol. 28, no. 2, pp. 1093–1102, May 2013.

[23] M. Vahid-Ghavidel, N. Mahmoudi, and B. Mohammadi-Ivatloo, “Self-scheduling of demand response aggregators in short-term markets based on information gap decision theory,” IEEE Trans. Smart Grid, vol. 10, no. 2, pp. 2115–2126, Mar. 2019.

[24] M. Kazemi, B. Mohammadi-Ivatloo, and M. Ehsan, “Risk-constrained strategic bidding of GenCos considering demand response,” IEEE Trans. Power Syst., vol. 30, no. 1, pp. 376–384, Jan. 2015.

[25] S. Shafiee, H. Zareipour, A. M. Knight, N. Amjady, and B. Mohammadi-Ivatloo, “Risk-constrained bidding and offering strategy for a merchant compressed air energy storage plant,” IEEE Trans. Power Syst., vol. 32, no. 2, pp. 946–957, Mar. 2017.

[26] H. Khalei, A. Abdollahi, and S. Nojavani, “Offering strategy of thermal-photovoltaic-storage based generation company in day-ahead market,” in Electricity Markets. Cham, Switzerland: Springer, 2020, pp. 113–133. [Online]. Available: https://link.springer.com/chapter/10.1007%2F978-3-030-36979-8_6

[27] P. Li, J. Ji, H. Ji, J. Jian, F. Ding, J. Wu, and C. Wang, “MPC-based local voltage control strategy of DGs in active distribution networks,” IEEE Trans. Sustain. Energy, early access, Mar. 7, 2020, doi: 10.1109/TSTE.2020.2981486.

[28] S. Yao, P. Wang, X. Liu, H. Zhang, and T. Zhao, “Rolling optimization of mobile energy storage fleets for resilient service restoration,” IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1030–1043, Mar. 2020.

[29] A. Das and Z. Ni, “A novel fitted rolling horizon control approach for real-time policy making in microgrid,” IEEE Trans. Smart Grid, early access, Jan. 15, 2020, doi: 10.1109/TSG.2020.2966931.

[30] J.-Y. Gotob and Y. Takano, “Newsvendor solutions via conditional value-at-risk minimization,” Eur. J. Oper. Res., vol. 179, no. 1, pp. 80–96, May 2007.

[31] K. Pažek and T. Rozman, “Decision making under conditions of uncertainty in agriculture: A case study of oil crop,” J. Poljopr., vol. 15, no. 1, pp. 45–50, 2009.

[32] (2020). System Advisor Model. [Online]. Available: https://sam.nrel.gov/

[33] J. Contreras, R. Espinola, F. J. Nogales, and A. J. Conejo, “ARIMA models to predict next-day electricity prices,” IEEE Power Eng. Rev., vol. 22, no. 9, p. 57, Sep. 2002.

[34] R. H. Iman, H. T. C. Pedro, and C. F. M. Coimbra, “Solar forecasting methods for renewable energy integration,” Prog. Energy Combustion Sci., vol. 39, no. 6, pp. 535–576, Dec. 2013.

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