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Strategic Bidding in the Presence of Renewable Sources for Optimizing the Profit of the Power Suppliers

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ABSTRACT The fast globalization of renewable energy-based technologies has enabled its wide speared utilization as well. This has shaped a new prospect of operation in the modern electricity system. But, its dependency on environmental factors leads to an uncertain scenario in the day-ahead electricity market. During this period, compromises are made in the genuine process of expenditure and resources of the producers to offset the capacity that decreases the profits for the producers. In general, a significant variety of scenarios need to be taken into account when describing uncertainty, thereby necessitating the need for techniques of scenario reduction. Therefore, to manage the intractable effects of solar radiation and wind speed instability, the function of the Beta and Weibull distribution of probability is implemented, respectively, and scenarios are minimized using forward-reduction algorithms. Besides, an underestimation and overestimation of the cost function are used to calculate the deviation of renewable influence. Thus, this paper is suggesting a valuable bidding strategy to maximize the remuneration of electricity producers in the presence of rival competitors and the instability of solar and wind energy. This problem has been prepared by taking the benchmark IEEE 30-bus network with and without renewable energy sources, and this problem has been solved by using the Gravitational Search Algorithm. The observations of the outcome demonstrate the appropriateness of the projected bid strategy in the presence of volatility of renewable energy.

INDEX TERMS Energy market, gravitational search algorithm, market clearing price, strategic bidding, solar power, wind power.

I. INTRODUCTION

In the electricity segment, deregulation leads to the establishment of a universal forum called the electricity market, which makes competition at all stages, from the seller to the procurer. In this type of electricity market, electricity suppliers send price and quantity bids for the selling of energy or services, potential buyers send bids to buy electricity services, and the duty of the ISO or PX to introduce competition and transparency between different market players. However, there are still some problems left to make it fully competitive such as oligopolistic market activities, market control violations, the elasticity of price demand, strategic bidding activities of different power producers, etc., [1]. The competition in the electricity market provides an opportunity for generating companies (GENCOs) to improve their bidding strategy in a way that maximizes their individual benefit. In competitive wholesale markets, generally, GENCOs maximize their revenues by strategically biding at, or very close to, their marginal production expenditure. However, in fact, due to its limited participants, the electricity market behaves more like an oligopoly market. Commonly, GENCOs are bid for their production on a price greater than the marginal expenditure to make a profit. When GENCOs are trying to take advantage of

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market imperfection by submitting their bids called on a price greater than the marginal rate, that activities of GENCOs are called strategic bidding of GENCO's [2].

In [3] firstly introduces the issues of the bidding strategy for GENCOs and several researchers have subsequently developed it. Modeled as a bi-level GENCO's competitive bidding problem optimization issue and solved using the method of Newton assuming maximum data on the bid of a competitor in [4]. An approach using repeated Monte Carlo (MC) Simulation to achieve the optimum GENCO bidding strategy is presented in [5]. MC technique repeatedly measures the best bidding strategy for one competitor with the offer of random rivals. As an optimal bidding solution, the standard value of the bidding constraint was measured. In the next round of the auction, reinforcement learning is used to obtain the best bid price for submission [6]. An inquiry into the best possible bidding strategy using stochastic dynamic programming with risk management for both the reserve and energy sectors is offered in [7]. Oligopolistic power markets are modeled as a nonlinear competitive situation, and the best possible bidding strategies are built using a dynamic approach depend on game theory [8]. In view of the fact that the power market is not fully viable, a plan to bid at the cost of some amount greater than the marginal production rate for GENCOs is addressed [9]. In [10], optimal bidding strategy with imperfect knowledge in which the bidding activity of rivals is projected using the support vector machine. A study is presented on the optimal number of bidding segments needed for GENCO's bidding strategies [11]. A model for obtaining best bidding for power suppliers that takes into account transmission congestion and the bidding actions of rivals is provided in [12]. A new bidding strategy model is presented based on bi-level optimization and risk measurement of CVaR [13]. A multi-agent structure is used to research the flawed market process, and a new concept of state behavior based on generalized Q-learning is proposed [14]. Given symmetrical and unsymmetrical data, the practical bidding strategy is presented in a Day-Ahead Market (DAM) [15]. A new risk-based decision-making method is introduced to achieve optimal GENCO bidding strategies accounting for short-term and long-term risk aversion preferences [16]. The bidding strategy issue of power providers considering the ramp rates of the generator in a DAM is projected in [17]. From the literature, it is concluded that the unpredictable bidding activities of competing producers generally affect the strategic bidding decision model process. As knowledge about the bidding activity of rivals is not known a priori, it can be approximated using historical data. In outlook of this explanation as a point of apprehension, the huge greater part of researchers used the normal probability function to model the actions of rivals and then work out the maximization of benefit for rival power producers using different heuristic and meta-heuristic algorithms. Researchers usually require three requirements to be met by a practical optimization technique. Firstly, the method should find the global solution irrespective of the parameter values of the initial system. Secondly, there should be rapid convergence. Third, a minimum number of control parameters should be available to the program to make it easy to handle. Heuristic and meta-heuristic techniques are depending on the modification of their parameters, and therefore the techniques with fewer modification parameters result in the majority of precise outcomes.

De-carbonization of the power sector led to the deployment of Renewable Energy Sources (RES) for clean power productions. Electricity generation outputs and percent of installed renewable plants capacity will increase and gradually become the main generators of electricity. Therefore, it is of amazing implication for the RE organizations to find out optimum bidding strategy for wind and solar units that take attention in the power market. In the existing literature, the pooled strategic bid of RES with conventional generators is modeled. Optimal strategic wind penetration bidding was considered in [18]–[23]. It is concluded from [18]–[23] that the uncertainty in wind power results in the output of power imbalances and increased expenses, thus reduces wind power incentives. By adding a penalty for deviations between real and expected power was tackled. Recently, robust methods [24] are used to correctly approximate wind power production. This study also suggested an efficient bidding strategy, integrating wind power to maximize the supplier's gain. The bidding strategy in [25]–[29] also included emerging renewable energy sources such as solar photovoltaics (SPVs). Those plays, however, did not find confusion associated with SPV. So for convincingly modeling solar prediction, a method is needed.

In this research work, a concerted strategic bid with the aims of benefit maximization with the amalgamation of RESs with conventional power supplies is suggested. Using the novel heuristic approach Gravitational Search Algorithm (GSA) [30]–[35], this problem was solved. GSA is well-established depending on gravity law and mass interactions with its application to a power system problem. Additionally, renewable is used as a probabilistic way of modeling uncertainty and underestimating and overestimating their predictive error in cost features.

II. MODELING OF RENEWABLE ENERGY SOURCES

When Modeling of RESs, namely solar and wind, is being established in this segment. Solar irradiation is based on the function of the Beta probability density (pdf) and the function of Weibull probability density (pdf) analysis of wind speed. More simulations employ distributions of power expectation obtained from the respective models.

A. MODELING OF SOLAR POWER

In the existence of solar power to contend with fair bidding, the instability associated with solar irradiation needs to be handled. Solar irradiation conversion is typically established on the temperature of the solar cell, the insolation of the solar cells, and the scientific characteristics of the diverse PV modules. It is possible to measure the solar power output by utilizing the irradiance of solar and solar cell temperature that can be expressed as [36]

$$T_{cell,t} = T_a + S_{i,t}\left(\frac{T_{NO}-20}{0.8}\right) \tag{1}$$

$$I_t = S_{i,t}\left[I_{sc} + I_{TK}\left(T_{cell,t}-25\right)\right] \tag{2}$$

$$V_t = V_{oc} - V_{TK} \times T_{cell,t} \tag{3}$$

$$S_{PO,t}\left(S_{i,t}\right) = n \times I_t \times V_t \times FF \tag{4}$$

$$\text{Here,}\quad FF = \frac{I_{mpp} \times V_{mpp}}{I_{sc} \times V_{oc}} \tag{5}$$

Due to known for its sun orientation implementation and minimal hour approachability, solar irradiance exists partial predictability. Evidence for solar irradiation is considered in this work from Barnstable City, Massachusetts, USA. It is noted that this evidence follows a Beta pdf as [37]

$$\begin{aligned} &B_{pdf}\left(S_{i,t}\right) \\ &= \left\{\frac{\Gamma\left(A_t+B_t\right)}{\Gamma\left(A_t\right)\Gamma\left(B_t\right)}\left(\frac{S_{i,t}}{S_{i\,\max,t}}\right)^{(A_t-1)}\left(1-\frac{S_{i,t}}{S_{i\,\max,t}}\right)^{(B_t-1)}\right\}, \\ &0 \le \left(\frac{S_{i,t}}{S_{i\,\max,t}}\right) \le 1,\ \mathrm{A}_t > 0,\ \mathrm{B}_t > 0 \end{aligned} \tag{6}$$

The value of the parameters (A_t, B_t) of Beta distribution measured using the mean (μ_{si}) and standard deviation (σ_{si}) of the historical details concerning irradiation of solar are as follows

$$A_t = \mu_{si}^2\left(\frac{1-\mu_{si}}{\sigma_{si}} - \frac{1}{\mu_{si}}\right) \tag{7}$$

$$B_t = A_t\left(\frac{1}{\mu_{si}} - 1\right) \tag{8}$$

In the meantime, Beta distribution variables are within the interval range of (0, 1). Therefore, $\left(\frac{S_{i,t}}{S_{i\,\max,t}}\right)$ is considered as a gross amount of Sunlight.

$$\begin{aligned} &B_{pdf}\left(S_{\mathrm{PV},t}\right) = \left\{\begin{array}{c} \frac{1}{S_{PV}^{\max}} \times \frac{\Gamma\left(A_t+B_t\right)}{\Gamma\left(A_t\right)\Gamma\left(B_t\right)}\left(\frac{S_{\mathrm{PV},t}}{S_{PV,t}^{\max}}\right)^{(A_t-1)} \\ \left(1-\frac{S_{PV,t}}{S_{PV,t}^{\max}}\right)^{(B_t-1)} \end{array}\right\}, \\ &0 \le \left(\frac{S_{\mathrm{PV},t}}{S_{PV,t}^{\max}}\right) \le 1,\ \mathrm{A}_t > 0,\ \mathrm{B}_t > 0 \end{aligned} \tag{9}$$

Thus, there is a random generation of 1000 beta distributed scenarios that is transformed into power scenarios, which suit the desired PV modules. Solar power also adheres to the Beta pdf principles

B. MODELING OF WIND POWER

In the existence of wind to contend with fair bidding, the instability associated with wind speed needs to be handled. Instability with wind speed is usually modeled by utilizing a two-parametric function called Weibull distribution [36]. The meanings are as follows:

$$W_{pdf} = \frac{k}{c}\left(\frac{v}{c}\right)^{(k-1)}\left(exp\left(-\frac{v}{c}\right)^k\right) \tag{10}$$

where shape factor and scale factor are k, and c, and v is wind speed (m/s). These parametric values can be estimated using known mean (μ_{hws}), and standard deviation (σ_{std}) are as follows [38]

$$k = \left(\frac{\sigma_{std}}{\mu_{hws}}\right)^{(-1.086)} \tag{11}$$

$$c = \left(\frac{\mu_{hws}}{\Gamma\left(1+\left({}^{1}\!/_{k}\right)\right)}\right) \tag{12}$$

Diverse scenarios are produced by utilizing wind velocity data, which is collected from anemometers. Anemometers are measure wind velocity in wind farms at different heights. To imitate similar patterns, first, Using the Weibull distribution, 1000 scenarios are generated randomly that are further changed into corresponding power scenarios to adequate hub heights. In certain cases, the heights of the center and the anemometers are not equivalent. In these conditions, the wind speed is estimated as [39]

$$v\left(h_{est}\right) = v\left(h_{rkh}\right)\left(\frac{h_g}{h_{kah}}\right)^{(\gamma)} \tag{13}$$

where $v\left(h_{est}\right)$ is estimated wind speed at appropriate turbine hub height; $v\left(h_{rkh}\right)$ is traced wind speed at acknowledged hub altitudes; h_g is generator wind turbine base height (m); h_{kah} is anemometer in place height, and γ is the shear coefficient parameter governing the irregularity and environment circumstance of the surface.

The measured wind velocities are changed into wind energy with a wind turbine energy curve. The energy curve is a relationship between wind speed and wind energy. May write the relationship as

$$W_a(v) = \begin{cases} 0 & \mathrm{v} \le \mathrm{v}_{in} \\ \frac{1}{2}\eta_p(v)\,\rho A_s v^3 & \mathrm{v}_{in} \le v \le v_r \\ W_r & \mathrm{v}_r \le v \le v_o \\ 0 & \mathrm{v} \ge \mathrm{v}_o \end{cases} \tag{14}$$

where $\eta_p(v)$, W_r and $W_a(v)$ are efficiency, rated output and available power at a given wind speed of wind generator respectively; ρ is the air density (kg/m^3); A_s is the rotor swept area of the wind turbine.

The produced wind energy inconsistent can be integrated into the distribution employing a power curve to predict the likelihood of wind power in a range of working zones.

Linear wind output probability can be defined as

$$\begin{aligned} f_w\left(\mathrm{v}_{in} \le v \le v_r\right) = \left(\frac{kzv_{in}}{cW_r}\right)\left[\frac{(1+zW_a/W_r)v_{in}}{c}\right] \\ \times\left\{-\left[\frac{(1+zW_a/W_r)v_{in}}{c}\right]^k\right\} \end{aligned} \tag{15}$$

Here

$$z = \frac{(v_r - v_{in})}{v_{in}}$$

The probability of zero wind production can be given as

$$f_w\,[(\mathrm{v} \le \mathrm{v}_{in}) \text{ and } (\mathrm{v} \ge \mathrm{v}_o)] = 1 - \exp\left[-\left(\frac{v_{in}}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \quad (16)$$

Finally, the rated wind output probability will be as follows

$$f_w(\mathrm{v}_r \le v \le v_o) = \exp\left[-\left(\frac{v_r}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \quad (17)$$

C. REDUCTION OF SOLAR AND WIND POWER SCENARIOS

There are 1,000 solar and wind scenarios formed. However, the possibility of some events may be extremely low; also, the odds of some situations may be the same. Subsequently, scrutinizing the scenarios is necessary to achieve substantially smaller number scenarios while ideal strategies of lesser and the same possibility. The diminution will be such that it does not change the stochastic properties. The number of decreased schemes builds upon the form and complexity of the difficulty to be optimized and should be concentrated to or below one-quarter of possibilities produced [39].

This used a methodology known as Kantorovich Distance Matrix (KDM) for scenario reduction [40]. This is based on the difference between the Euclidian possibilities and their related probabilities. This reduced the nearest and lowest-probability scenarios. These are the steps that are used to measure the KD matrix.

Step I: For every case, measure the Euclidian distance to other imaginable circumstances. Of any two separate possibilities υ^i and υ^j distance is calculated as

$$KD\left(\upsilon^i, \upsilon^j\right) = \left(\sum_{l=0}^{\eta_l} \left(v_l^i - v_l^j\right)^2\right)^{\frac{1}{2}} \quad (18)$$

Step II: Locate the nearest minimum detachment min $\left\{KD\left(\upsilon^i, \upsilon^j\right)\right\}$ for each possibility υ^i to the possibility υ^j, j $\neq$ i.

Step III: Reproduce or multiply with corresponding probability obtained in Step II

$$\min\left\{KD\left(\upsilon^i, \upsilon^j\right)\right\} \times P\left[\upsilon^i\right] \quad (19)$$

Step IV: Reduce the least gap and little possible scenario. Then apply the likelihood of the eliminated scenario to the next closest scenario.

Step V: Do again Step II-IV until the criterion of stoppage has reached.

D. ASSESSMENT OF THE QUANTITY OF SOLAR AND WIND ENERGY AVAILABLE FOR BIDDING

KDM is utilized to obtain the expected solar (S_g), and wind (W_g) energy, and the correct probabilities are determined as follows

$$S_g = \sum_{i=1}^{\upsilon_i} S_{ai} \times \mathrm{prob}_i \quad (20)$$

$$W_g = \sum_{i=1}^{\upsilon_i} W_{ai} \times \mathrm{prob}_i \quad (21)$$

here prob_i is the possibility of decreased i^{th} generated scenario.

E. AN ASSESSMENT OF WIND AND SOLAR ENERGY COSTS

Naturally unpredictable in the environment are wind and solar power, contributing to variance in day-to-day forecasting and actual power production. Therefore, underestimation (real energy is extra than projected energy) and overestimation (effective energy is a smaller amount than expected) of wind energy are persistent. For network operator-owned solar and wind generation, this state of mismatch can be integrated as unbalance term in the cost function. This wind and solar imbalance calculate the difference in the forecast and actual electricity, summing up the cost of underestimation and overestimation. It can be represented as [36]

$$IMC(\mathrm{Sg}_n) = O_c(\mathrm{S}_g) + U_c(\mathrm{S}_g) \quad (22)$$

$$IMC(\mathrm{Wg}_n) = O_c(w_g) + U_c(w_g) \quad (23)$$

where, $O_c(w_g)$ and $O_c(\mathrm{S}_g)$ represent the overestimation cost, $U_c(w_g)$ and $U_c(\mathrm{S}_g)$ represents the cost of underestimating the wind and solar energy available, respectively.

Both type estimation for the available solar and wind energy are possible and measured as follows:

F. AN ASSESSMENT OF OVERESTIMATED RENEWABLE (SOLAR AND WIND) ENERGY PRODUCTION

The power deficit is a deciding factor in determining the expenditure of overestimating renewable (solar and wind) energy and the chance of deficiency for a given quantity of intended renewable (solar and wind) energy. And it could be described as

$$O_c(\mathrm{S}_g) = \mathrm{K}_o * \int_0^{S_g} (\mathrm{S}_g - S_a) * f_{S_a}(\mathrm{S}_a) * dS_a \quad (24)$$

$$O_c(w_g) = \mathrm{K}_o * \int_0^{W_g} (W_g - W_a) * f_{W_a}(W_a) * dW_a \quad (25)$$

where K_o is the penalty coefficient for overestimating power.

G. AN ASSESSMENT OF UNDERESTIMATED RENEWABLE (SOLAR AND WIND) ENERGY PRODUCTION

The probability of underestimation is dependent on the calculation of the real surplus renewable (solar and wind) production and the possibility of surplus energy prevalence. It does not, however, reflect exact costs but instead reflects a penalty word for the wastage of available investment.

$$U_c(\mathrm{S}_g) = \mathrm{K}_u * \int_{S_g}^{S_{\max}} (\mathrm{S}_a - S_g) * f_{S_a}(\mathrm{S}_a) * dS_a \tag{26}$$

$$U_c(w_g) = \mathrm{K}_u * \int_{W_g}^{W_{\max}} (W_a - W_g) * f_{W_a}(W_a) * dW_a \tag{27}$$

where K_u is a fine for the lack of situational advantages per \$/kWh owing to underestimating the capacity.

III. STRATEGIC BIDDING FORMULATION IN THE PRESENCE OF RENEWABLE SOURCES

Suppose that every power supplier (PS) is needed to send a bid to POOL as a non-decreasing linear supply feature in a single-sided POOL-based energy market and the running cost function of any generating unit as

$$\mathrm{PC}_m(\mathrm{Pg}_m) = a_m Pg_m + b_m Pg_m^2 \tag{28}$$

here, m is the number of PS; bid parameters of the m$^{\text{th}}$ PS are a_m and b_m; and Pg_m is the active power quantity of the m$^{\text{th}}$ PS.

In a single-side bid model, the m$^{\text{th}}$ PS submits the non-decreasing linear supply bid function as:

$$CP_m(\mathrm{Pg}_m) = \pi_m + \phi_m Pg_m, \quad m = 1, 2, \ldots\ldots, \mathrm{CPS} \tag{29}$$

where π_m and ϕ_m are bid coefficients that be required to non-negative.

If the PS offers have been completed and submitted to ISO, the ISO compares the power supply with the overall demand of the system. After the matching, ISO decided the market-clearing price (MCP) and cleared the marketplace. Bid function, power balance constraint, and power inequality constraint of the m$^{\text{th}}$ PS is given in equation (30) to (32).

$$\pi_m + \phi_m Pg_m = R \tag{30}$$

$$\sum_{m=1}^{cps} Pg_m + \sum_{n=1}^{sg} sg_n + \sum_{n=1}^{wg} Wg_n = Q(\mathrm{R}) \tag{31}$$

$$Pg_{\mathrm{min,m}} \leq Pg_m \leq Pg_{\mathrm{max,m}} \tag{32}$$

where the MCP is R, the projected load by the market operator is $Q(\mathrm{R})$. Let us supposed that

$$Q(\mathrm{R}) = L_c - k^*\mathrm{R} \tag{33}$$

where L_c is constant and $\mathrm{k} = 0$ is non - negative load price elasticity.

For deciding MCP and calculation of the amount of bid power, ISO considered equations (30) and (31) and ignored the equation (32). The MCP and amount of bid power is calculated as equation (34) and (35) respectively.

$$R = \frac{L_c - \sum_{n=1}^{sg} Sg_n - \sum_{n=1}^{wg} Wg_n + \sum_{m=1}^{cps} \frac{\pi_m}{\phi_m}}{k + \sum_{m=1}^{cps} \frac{1}{\phi_m}} \tag{34}$$

$$Pg_m = \frac{R - \pi_m}{\phi_m} \tag{35}$$

If the amount of bid power in equation (35) exceeds its limits, it will be fixed as equation (32).

After the calculation of MCP and the amount of bid power, we can calculate the profit of the m$^{\text{th}}$ PS. Therefore, in this work, the key role of the goal is to maximize the profit of the m$^{\text{th}}$ PS in the presence of renewable PS as given in equation (36)

Maximize

$$\begin{aligned} F(\pi_m, \phi_m) = {} & R \times \mathrm{Pg}_m - PC_m(\mathrm{Pg}_m) + R \times \mathrm{Wg}_n \\ & - IMC(\mathrm{Wg}_n) + \mathrm{R} \times \mathrm{Sg}_n - IMC(Sg_n) \end{aligned} \tag{36}$$

Subject to: equation (20), (21), (22), (23), (28), (34), and (35)

Generally, in the sealed bidding process, the bidding information is kept confidential. But bidding information of the previous bidding process can be obtained. In the light of this information, PS's can guess about the market-clearing and estimated the MCP. Therefore, each PS tries to guess the bidding method and behavior of other suppliers. But they face problems when they try to guess rival's behavior. Due to the interrelation of bid parameters, PS's used the joint probability distribution function (pdf) as given in equation (37) for guessing rival's behavior.

$$\begin{aligned} \mathrm{pdf}(\pi_m, \phi_{\mathrm{m}}) = {} & \frac{1}{2\pi \sigma_m^{(\pi)} \sigma_{\mathrm{m}}^{(\phi)} \sqrt{1 - \rho_{\mathrm{m}^2}}} \times \exp\left\{ -\frac{1}{2\left(1 - \rho_{\mathrm{m}}^2\right)} \right. \\ & \times \left[\left(\frac{\pi_{\mathrm{m}} - \mu_{\mathrm{m}}^{(\pi)}}{\sigma_{\mathrm{m}}^{(\pi)}} \right)^2 + \left(\frac{\phi_m - \mu_{\mathrm{m}}^{(\phi)}}{\sigma_m^{(\phi)}} \right) \right. \\ & \left. \left. \times \; - \frac{2\rho_m \left(\pi_m - \mu_m^{(\pi)}\right) \left(\phi_m - \mu_m^{(\phi)}\right)}{\sigma_m^{(\pi)} \sigma_{\mathrm{m}}^{(\phi)}} \right] \right\} \end{aligned} \tag{37}$$

This pdf can be displayed as a compact form

$$(\pi_m, \phi_m) \sim N \left\{ \begin{bmatrix} \mu_m^{(\pi)} \\ \mu_m^{(\phi)} \end{bmatrix}, \begin{bmatrix} (\sigma_m^{(\pi)})^2 & \rho_m \sigma_m^{(\pi)} \sigma_m^{(\phi)} \\ \rho_m \sigma_m^{(\pi)} \sigma_m^{(\phi)} & (\sigma_m^{(\phi)})^2 \end{bmatrix} \right\} \tag{38}$$

Here, the collective distribution parameters are $\mu_m^{(\pi)}$, $\mu_m^{(\phi)}$, $\sigma_m^{(\pi)}$ and $\sigma_m^{(\phi)}$, the coefficient of correlation between π_m and ϕ_m is ρ_n. $\mu_m^{(\pi)}$ and $\mu_m^{(\phi)}$ are the mean and $\sigma_m^{(\pi)}$ and $\sigma_m^{(\phi)}$ are the standard deviations of the π_m and ϕ_m respectively.

IV. GRAVITATIONAL SEARCH ALGORITHM

GSA for solving non-differentiable and nonlinear optimization problems was suggested in [31]. The solution procedure of the problem using GSA as a flowchart is shown in figure 1.

A. INITIALIZATION OF POPULATION

Suppose a structure consisting of N agents (masses) which reflect the k$^{\text{th}}$ agent's position

$$\lambda_k = (\lambda_k^1, \ldots\ldots, \lambda_k^D, \ldots\ldots., \lambda_k^M) \;\; \text{For} \;\; k = 1, 2, \ldots\ldots.., N \tag{39}$$

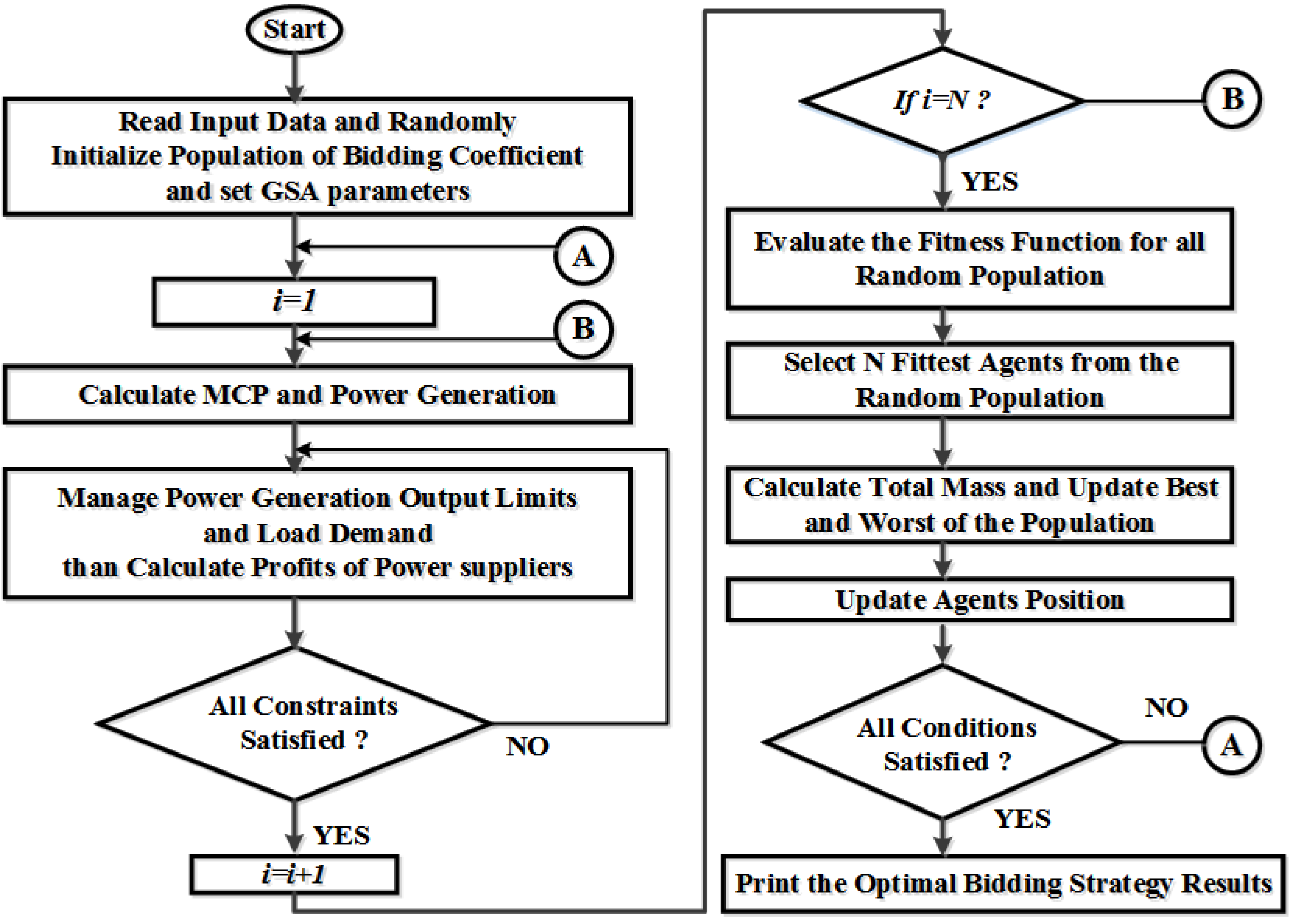

FIGURE 1. Approach to solutions as a flowchart.

where $\lambda_k^D \in [L_k^D, U_k^D]$, $D = 1, 2\ldots\ldots, M$, is the kth representative location in the Dth measurement, and M is the dimension of search space and L_k^D, U_k^D are lower bound and upper bound limits of kth agents in the Dth dimension.

B. CALCULATION OF FITNESS

The most excellent result of equation (36) is assumed as a fitness function fit_z here.

C. AGENTS ACCELERATION

The estimation of fitness is used to measure the weight of any agent in GSA. The mass of each agent is determined according to the following

$$M_k(i) = \frac{m_k(i)}{\sum_{l=1}^{N} m_l(i)} \tag{40}$$

here,

$$m_k(i) = \frac{fit_k(i) - worst(i)}{best(i) - worst(i)}$$

where $M_k(i)$ is the normalized mass of kth representative at ith iteration and $worst(i)$, $best(i)$ are the bad and best fitness of all agents at ith iteration. The acceleration $a_k^D(i)$ acting on kth agent at iteration i is evaluated as follows:

$$a_k^D(i) = \sum_{\substack{l \in Gbest, \\ l \neq k}} rand_l \quad G(i)\, \frac{M_k(i)}{R_{kl}(i)+E}(\lambda_l^D(i) - \lambda_l^D(i)) \tag{41}$$

where a place of the first 2 percent of agents is *Gbest* by means of the highest fitness value and best considerable mass, $rand_l$ is the standardized number of random intervals between [0, 1], $R_{kl}(i)$ is the Euclidean distance of two agents kth and lth at ith iteration and E is a small positive constant. The gravitational characteristic G(i) is calculated as

$$G(i) = G \times \left(1 - \frac{iteration}{Total\ iteration}\right) \tag{42}$$

here,

$$G = c \max_{D \in \{1,2,\ldots\ldots,M\}} \left(\lambda_U^D - \lambda_L^D\right)$$

where c is explored space limitation.

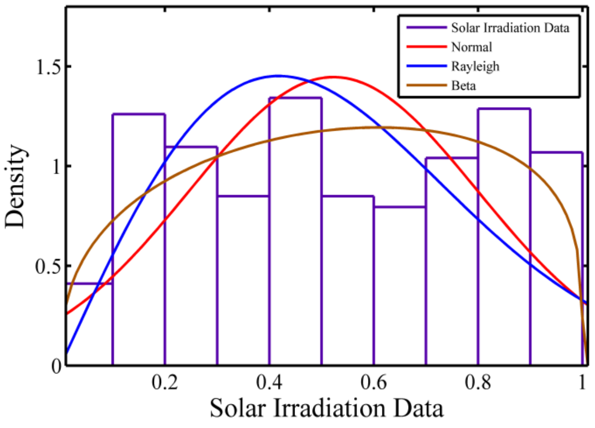

FIGURE 2. Solar irradiation for diverse PDFs.

D. UPDATE VELOCITY AND LOCATION OF THE AGENTS

After that (i+1)th iteration the velocity and location of the agents are considered as follows

$$\begin{cases} v_k^D(i+1) = rand_k \times v_k^D(i) + a_k^D(i) \\ \lambda_k^D(i+1) = \lambda_k^D(i) + v_k^D(i+1) \end{cases} \tag{43}$$

where $rand_k$ is a random number among space [0, 1], $v_k^D(i)$ is the velocity of kth agent at Dth measurement at some stage in ith iteration and $\lambda_k^D(i)$ is the location of kth agent at Dth measurement at some stage in ith iteration.

V. RESULT AND DISCUSSION

In the objective of increasing the profit of the mth PS in the presence of renewable PSs, the IEEE 30-bus test system is considered in the suggested strategy, and data of the system is taken from [24] and presented in Table 1. In this mechanism, the evaluation is performed and evaluated first. Also, the model under consideration is updated to fit single solar and single wind energy producers to the scope of the impact of the renewable sources. One solar and wind provider of each 200 MW rated power is considered. The proposed terminology is settled by GSA on a 3.20 GHz, i5 processor, 4GB RAM PC, and MATLAB R2014a.

TABLE 1. IEEE 30-bus system data.

Number of Conventional Suppliers	Range of Power Despatches		Production Cost Parameters	
	Pg_{min} (MW)	Pg_{max} (MW)	a	b
1	20	160	2.0	0.00375
2	15	150	1.75	0.0175
3	10	120	1.0	0.0625
4	10	100	3.25	000834
5	10	130	3.0	0.025
6	10	130	3.0	0.025

TABLE 2. PV module specifications.

Module Characteristics	Unit
PV^{max} (Peak Output)	340 Watt
I_{TK}	0.047 mAmp./^{0}C
V_{TK}	0.335 mVolt./^{0}C
FF (Fill Factor)	0.755
T_a and T_{NO} (Ambient Temperature and Nominal Cell Operating Temperature)	25^0 C and 46^0 C
I_{mpp} (Curret at Maximum Power)	8.99 Amp.
V_{mpp} (Voltage at Maximum Power)	37.8 Volt.
Open Circuit Voltage ($V_{oc)}$)	46 Volt.
Short Circuit Current ($I_{sc)}$)	9.78 Amp.

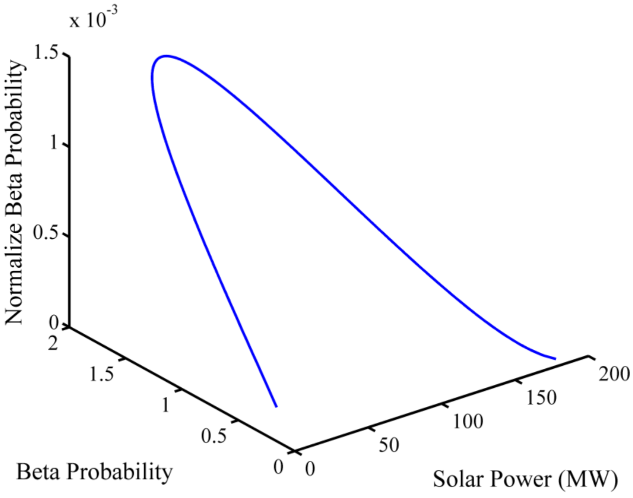

FIGURE 3. Probabilities of beta PDF and normalized beta PDF.

Single hour (1300-1400 hrs) solar irradiation data from Barnstable City, Massachusetts, USA, 1 January to 31 December 2013 is taken as analysis [41] turning to solar energy estimate. Sun-irradiation is transformed to solar power using the requirements of the PV module [36] and shown in Table 2. The data on Sun-irradiation is placed of diverse distributions of probability and shown in Figure 2.

The Log Probability, Mean, and Variance standards are determined by utilizing different distributions and given in table 3. It is worthy of mention that the standard Log Probability of Beta distribution is superior to considered other distributions that indicate ideally suited results for the distribution.

For historical solar irradiation results, the standards of the Beta distribution coefficients, A and B are 1.3909 and 1.2518 correspondingly and calculated using equations (7) and (8), respectively. Then, using PV module specifications, a thousand possibilities of solar irradiation are created and changed to power possibilities. The respective produce scenarios by utilizing Beta PDF assign a normalized probability to construct their outline equal to unity. The actual probabilities of Beta and normalized Beta PDF for produce scenarios are shown in Figure 3.

Wind speed data for one hour (1300-1400 hrs) from Barnstable City, Massachusetts, US for 1 August to 31 August 2005 [42] is used as study for the wind power estimate. The value of the air thickness and the shear parameter is 1.242 kg / m3, and 0.35. To produce wind power, the wind turbine

TABLE 3. Values of different parameters related to respective PDFs of solar irradiation.

	Beta Fit	Rayleigh Fit	Normal Fit
Mean	0.526305	0.523565	0.52266
Variance	0.06844	0.0749005	0.0760555
Log Likelihood Value	10.1446	-34.9839	-47.2392

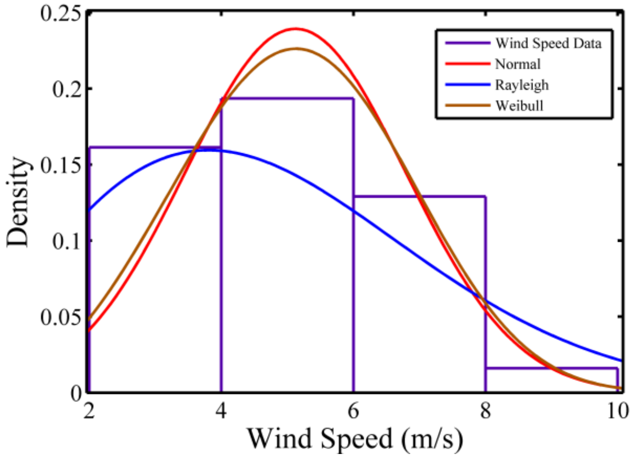

FIGURE 4. Wind speed for diverse PDFs.

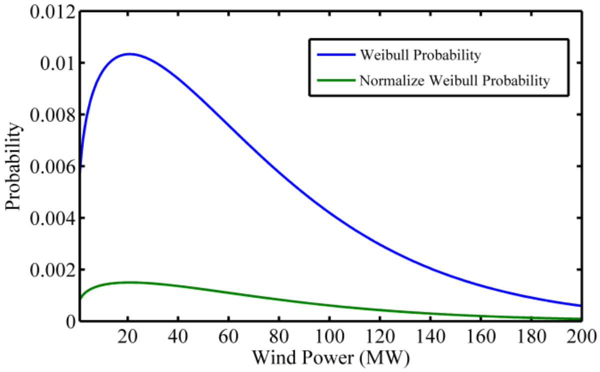

FIGURE 5. Probabilities of weibull PDF and normalized weibull PDF.

VENSYS-100 and the 2.5 MW output generators are situated at a hub height of 100 meters [43]. The data on wind speed is placed into different distributions of probability and shown in Figure 4.

The Log Probability, Mean, and Variance standards are determined by utilizing different distributions and given in table 4. It is worth mentioning that the standard Log Probability of Weibull distribution is superior to considered other distributions, which indicate ideally suited results for the distribution.

Shape and scale parameters values 3.34 and 7.93 m/s are calculated using (11) and (12) correspondingly. A thousand wind speed scenarios are then constructed, and the relationship involving wind power and wind velocity is translated into power scenarios. The respective produce scenarios by utilizing Weibull PDF assigns a normalized probability to construct their outline equal to unity. Weibull and the function of probability density normalization for developed wind power scenarios are shown in Figure 5.

TABLE 4. Values of different parameters related to respective PDFs of wind speed.

	Weibull Fit	Rayleigh Fit	Normal Fit
Mean	5.12102	4.76584	5.12151
Variance	2.8617	6.20614	2.77917
Log Likelihood Value	-59.2297	-64.7905	-59.3305

In view of the fact that the huge quantity of forecasted possibilities of the wind and solar instability. There are, however, a small number of cases that show the matching consideration. Therefore, KDM [39] approach is also used to remove these possibilities for enhanced renewable energy modeling. In this 10 decreased possibilities are produced using 1000 wind and solar possibilities specified respectively in Table 5 and Table 6. The estimated power values for wind and solar are 49.54 MW and 73.29 MW correspondingly, centered on the absolute importance of wind and solar productions and their particular probability.

In the solution process of suggested bidding, bidding coefficients interdependencies are calculated by considering one coefficient as unchanging and the second coefficient is searched in the search space as specified in [5] by utilizing GSA optimization method. Moreover, the values of the PDF function parameters of equation (23) are considered the same as [5]. The proposed optimal bidding strategies are investigated using Gravitational Search Algorithm (GSA) and the optimum values for coefficients of bidding are given in Table7 for without RES integration, with wind only, with solar only, and with wind-solar both.The considered bidding strategies to comprehensible the market clearing prices (MCPs) for the benchmark IEEE 30-bus test network is considered using GSA-predicted bidding coefficients, and their corresponding earnings, as well as individual generator despatch are calculated.

Sound effects of RES integration are consecutively measured on the IEEE 30-bus system. In support of bidding strategies of RES integration, the coordination operator is permitted to modify the forecasted demand; in this way, forecasted demand is not included with RES production and then modified the bid parameters in compliance with the current demand [18]. Depending on this method, the current MCP is assumed to be defined by RES production. In case first, without RES integration, MCP is calculated; therefore, in the second case, consideration is given to the wind production, and fresh MCP is determined by revising the parameters of bidding by adjusted demand. Correspondingly, in third case, MCP is viewed with the addition of solar production, and eventually, in the fourth case, the combined benefits with both wind and solar productions. The considerations of running costs for both RESs were not considered in bidding strategies with RES integrations. Nonetheless, due to the intermittency linked with these RESs, it is appropriate to

TABLE 5. Kantorovich Distance Matrix (KDM) for final ten reduced solar power scenarios.

No.	1	2	3	4	5	6	7	8	9	10	Sa (MW)	Prob.	Min (KD)
1	0	11.42	34.23	46.35	62.47	80.47	98.7	114.8	131.1	150.2	16	0.022218	11.42
2	11.42	0	22.81	34.93	51.05	69.31	87.28	103.4	119.7	138.8	27.42	0.075345	11.42
3	34.23	22.81	0	12.12	28.24	46.5	64.47	80.60	96.85	116	50.23	0.268311	12.12
4	46.35	34.93	12.12	0	16.12	34.38	52.35	68.49	84.73	103.9	62.35	0.163971	12.12
5	62.47	51.05	28.24	16.12	0	18.27	36.23	52.37	68.62	87.76	78.47	0.277874	16.12
6	80.73	69.31	46.50	34.38	18.27	0	17.97	34.1	50.35	69.49	96.74	0.09117	17.97
7	98.7	87.28	64.47	52.35	36.23	17.97	0	16.13	32.38	51.53	114.7	0.046975	16.13
8	114.8	103.4	80.6	68.49	52.37	34.10	16.13	0	16.25	35.39	130.8	0.042748	16.13
9	131.1	119.7	96.85	84.73	68.62	50.35	32.38	16.25	0	19.14	147.1	0.00999	16.25
10	150.2	138.8	116	103.9	87.76	69.49	51.53	35.39	19.14	0	166.2	0.001399	19.14

TABLE 6. Kantorovich Distance Matrix (KDM) for final ten reduced scenarios of wind power.

Index	1	2	3	4	5	6	7	8	9	10	Wa (MW)	Prob.	Min (KD)
1	0	27.85	51.7	76.35	92.08	108.9	127.1	141.2	164.8	179.5	14.39	0.234229	27.85
2	27.85	0	23.85	48.5	64.23	81.06	99.26	113.4	136.9	151.6	42.24	0.443626	23.85
3	51.70	23.85	0	24.65	40.37	57.21	75.41	89.52	113.1	127.8	66.09	0.17126	23.85
4	76.35	48.5	24.65	0	15.73	32.56	50.76	64.87	88.43	103.1	90.74	0.080668	15.73
5	92.08	64.23	40.37	15.73	0	16.84	35.04	49.15	72.71	87.40	106.5	0.025689	15.73
6	108.9	81.06	57.21	32.56	16.84	0	18.20	32.31	55.87	70.56	123.3	0.025047	16.84
7	127.1	99.26	75.41	50.76	35.04	18.20	0	14.11	37.67	52.36	141.5	0.011009	14.11
8	141.2	113.4	89.52	64.87	49.15	32.31	14.11	0	23.56	38.25	155.6	0.005085	14.11
9	164.8	136.9	113.1	88.43	72.71	55.87	37.67	23.56	0	14.69	179.2	0.002536	14.69
10	179.5	151.6	127.8	103.1	87.39	70.56	52.36	38.25	14.69	0	193.9	0.000852	14.69

think about their cost of imbalances considerations. The cost is estimated in conditions of solar and wind productions are overestimation and underestimation. And the impact of this advantage is expressed in the overall revenue received by RES producers, minus the expense of the imbalance. The penalty parameter and reserve parameter related separately to underestimation and overestimation are measured to be 50 percent of MCP and equal to MCP correspondingly [24]. In table 7, results for considered different bidding strategies are given, and the result shows that in the case of without RES integration, MCP is \$13.94/MW, total traditional conventional power suppliers (CPS) production is 500 MW, and overall income with CPSs is \$5212.6. If CPS contains only wind power, then MCP is concentrated to \$12.48/MW, and the total CPS output is concentrated to 450.46 MW. In comparison, CPS net income is also substantially decreased by \$4116.8, which is attributed to the lower valuation of MCP and the replacement of traditional systems. The cost of wind production overall income, overestimation and underestimation is respectively \$219.02, \$44.94, and \$399.25. In the next considered case only solar production with CPS production, the overall income, overestimation and underestimation costs are 512.6355, \$114.7551, and \$248.4213, respectively. Moreover, the MCP is 11.95 \$/MW with a total output of CPS 426.71 MW, which is lesser than without RES integration and wind due to substantial solar production. In last case, the CPSs combined with both wind and solar productions are considered, in this case MCP is 11.33 \$/MW, which is much lesser than amongst all earlier measured cases. From the results for considered bidding strategies, the authors concluded that all the procure bids would convince by the lesser MCP, and the integrations of RESs would reduce the CPSs load. Reduction of CPSs despatch shows that the dependency of CPS is reduced considerably in power system operation. Also, this will be helping in the reduction of carbon emissions in the environment. Moreover, handling of uncertainty related

TABLE 7. Considered bidding strategies results with and without renewable integration.

Power Suppliers	π_m	Without any RES Integration			With Wind Only			With Solar Only			With Both Wind and Solar		
		ϕ_m	Pg (MW)	Profit ($)	ϕ_m	Pg (MW)	Profit ($)	ϕ_m	Pg (MW)	Profit ($)	ϕ_m	Pg (MW)	Profit ($)
1	2.0	0.049231	160	1815.32	0.049575	160	1580.7	0.049575	160	1495.4	0.04987	160	1396.7
2	1.75	0.224134	77.45	839.65	0.215113	60.15	582.1	0.215113	55.53	512.23	0.209055	51.24	444.8
3	1.0	0.722945	40.95	425.33	0.453362	35.6	329.44	0.453362	32.27	288.17	0.723917	19.68	179.1
4	3.25	0.097653	100	986.18	0.104385	98.7	829.65	0.104385	91.44	725.46	0.11051	78.52	583.0
5	3.0	0.289934	60.80	573.06	0.251243	48	397.46	0.251243	43.74	343.46	0.292762	33.86	253.4
6	3.0	0.289934	60.80	573.06	0.251243	48	397.46	0.251243	43.74	343.46	0.292762	33.86	253.4
MCP		13.9458			12.48			11.95			11.33		
Total Profit for TPS ($)		5212.6			4116.8			3708.22			3110.4		
Total Generation for TPSs (MW)		500			450.46			426.71			377.17		
Wg (MW)		00			49.5406			00			49.5406		
$O_c(w_g)$ ($)		00			44.9355			00			40.7919		
$U_c(w_g)$ ($)		00			354.3112			00			321.6396		
$IMC(\mathrm{Wg}_n)$ ($)		00			399.2468			00			362.4316		
Profit for WPS ($)		00			219.0199			00			198.8238		
Sg (MW)		00			00			73.2897			73.2897		
$O_c(\mathrm{S}_g)$ ($)		00			00			114.7551			108.8013		
$U_c(\mathrm{S}_g)$ ($)		00			00			248.4213			235.5325		
$IMC(\mathrm{Sg}_n)$ ($)		00			00			363.1764			344.3338		
Profit for SPS ($)		00			00			512.6355			486.0385		

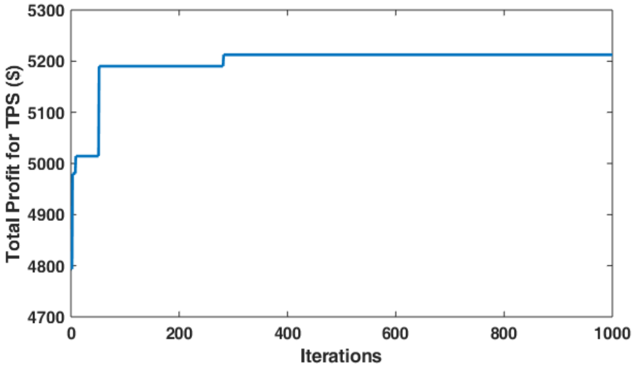

FIGURE 6. Convergence of GSA without renewable.

to RESs decreases the overestimations and will help fix the output of RESs for bidding in the market. In addition, this would allow suppliers of RES to give additional power to the real-time market if they fix their output and save penalties related due to the uncertainty.

The solution time cost without renewable energy solution for GSA is 4.58 seconds, and the convergence is shown in figure 6.

VI. CONCLUSION

This work suggested the most profitable bidding strategies for power producers to maximize their benefit with an amalgamation of RESs. RESs such as wind and solar are modeled using probabilistic approaches such as Weibull and Beta PDF and convert them into electrical power. Besides, this power was integrated as overestimation and underestimation terms in the cost model to consider the uncertainty of power production. In order to mitigate competitor dynamics in the power market, the suggested approach measures the rival's behavior using the normal PDF. Results for suggested bidding show that deployment of renewable sources impacts the offer, such as it decreases the CPS output and provides lowered MCP. This will attract the consumers to purchase the electricity and encouraged the producers the reduce carbon emissions. Moreover, handlings of uncertainty are very helpful to RESs for deciding their output for bidding and save penalties. Thus, concerning the uncertainty model of renewable sources, the current approaches can produce acceptable outcomes.

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