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Double-sided bidding strategy for power suppliers and large buyers with amalgamation of wind and solar based generation in a modern energy market

Satyendra Singh^{1,2} ✉, Manoj Fozdar¹

¹Department of Electrical Engineering, Malaviya National Institute of Technology Jaipur, J. L. N. Marg, Jaipur, Rajasthan, India

²School of Electrical Skills, Bhartiya Skill Development University, Jaipur, India

✉ E-mail: satyendagur@gmail.com

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Abstract: The deployment of renewable energy sources has been rapidly increasing due to environmental constraints but renewable electricity suppliers face an inevitable problem of uncertainty which is caused by the intermittent nature of renewable sources. In real-time operation, compromises have been made in cost and power to balance the power which reduces supplier benefits. Therefore, the functions of Weibull and Beta distribution of probability are used to handle the adverse impact of wind speed uncertainty and solar irradiation, respectively, and scenarios are reduced using the forward-reduction algorithm. Moreover, to measure the deviation of renewable power, underestimation and overestimation cost functions are utilised. This study proposes a suitable double-sided strategic bidding problem as a multi-objective optimisation problem to maximise the profits of suppliers and buyers to minimise uncertainty of rivals and renewable power. The formulated problem is solved by Technique for Order of Preference by Similarity to Ideal Solution along with Gravitational Search Algorithm, and simulation results are obtained in absence and presence of both solar and wind power on IEEE standard 30-bus and 57-bus test systems. The obtained results prove the suitability of the proposed bidding strategy in the presence of uncertainty of solar and wind power.

1 Introduction

The transformation of global electricity market into deregulated structures is continuously in progress since 1980. It encouraged innovative technologies to create a competitive market structure to improve the economy of trading [1]. The main principle of this transformation of electricity market is the designing of new open market model that is Pool-Co model for flexible electricity trade to achieve better economic efficiency. In these models, sealed bids are organised, applicants submit their bids to sell/purchase electricity to/from system operator, who decides the market clearing price (MCP). In this situation, participants construct their bids for exploiting their expected profits. However, unpredicted deviations in electricity market lead to imperfection in trading of electricity. Therefore, participants take advantage of these imperfections by bidding to increase their profit [2].

In the literature, extensive work has been attempted by the researchers on the problem of strategic bidding for maximising the profits of suppliers. The optimal strategic bidding problem was first time solved by dynamic programming based method for competitive suppliers in deregulated electricity market [3]. There are several factors that may affect these bidding strategies which mainly are demand fluctuation, generator production cost, some regulatory restrictions or operating constraints and bidding behaviour of other participants. In this bidding behaviour of rival suppliers in decision making of bidding with objective of profit maximisation is mostly being used in the literature [4–10]. In this procedure, rivals behaviour is modelled using normal probability distribution functions [4] and then the profit maximisation problem is solved using an appropriate algorithm some of these are particle swarm optimisation (PSO) algorithms [5], PSO combined with simulated annealing [6], bat-inspired algorithm [7], oppositional gravitational search algorithm [8], shuffled frog leaping algorithm (SFLA) [9] and bacteria foraging optimisation, [10]. Furthermore, block bid function and uncertain MCP [5], supply function equilibrium and pay as bid [6], linear bid function and uniform MCP [7–9] have been considered to solve strategic bidding problem. The strategic bidding was also modelled as a bi-level

optimisation problem, in which the problem of outer layer optimisation represents the maximisation of profit for the suppliers and the problem inner layer optimisation represents market clearing [10]. It is concluded that, the applications of heuristic algorithms to acquire the goal of optimal strategic bidding problem results motivate authors to apply more suitable heuristic technique.

During the recent years, the renewable energy usage around the globe has been on the upward swing due to low carbon emission. Electrical power productions and percent of installed capacities of wind and solar power plants go higher and will turn into the significant power generators soon. This has led to new dimensions of exploration in optimal bidding strategy with amalgamation of wind and solar based power generation. In this context, optimal strategic bidding with wind penetration have been considered in [11–16]. These mainly focus on strategy to tackle wind uncertainty by introducing a penalty function to minimise the power imbalance due to deviation from forecasted power, though it lowered the revenue of wind power. Recently, in [17] production of wind power is correctly approximated using robust method. Also, this work proposed optimal bidding strategy with inclusion of wind power to maximise the profit of supplier. Other renewable power sources such as solar photovoltaics (SPVs) have also been considered in bidding strategy [18–22]. However, these works have not considered uncertainty associated with SPV. Thus, a method is required to model solar prediction in a convincing way.

In the literature, most of the researchers have focused on supplier's side strategic bidding problem; limited work has been carried out on the demand side. In this, Wen and David [23] have attempted double sided strategic bidding problem considering power suppliers and large consumers. While Ding *et al.* [24] have considered a demand side bidding between elastic consumers and load serving entities (LSEs) for allocating demand response rewards to the customers while maximising LSEs profits. Thus to solve a double sided problem requires a multi-objective formulation where both entities are simultaneously optimised. In such state, power suppliers try to increase the MCP by withholding capacity from the market and the large buyers try to decrease the

MCP by adjusting their power consumption. Since these objectives are contradictory, therefore, a multi-objective problem design is essential. In the literature, researchers have developed several multi-objective solutions to deal with power system optimisation problems. Note that a single algorithm cannot meet the requirement to solve multi-objective optimisation problems. Therefore, the hybrid optimisation algorithm has been developed and reported in scientific literature [25–27]. In hybrid optimisation category, the most recent approach is, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and it is proposed in [28, 29] to provide best compromising solutions. This method can be combined with any recent heuristic optimisation method at some point of technique iterations to select the best compromising result. Notably, TOPSIS is now considered to be one of emerging method to solve multi-objective problems. It employs the Euclidian geometry to measure the distance of solutions from its best solution. It generates more evenly Pareto front compared to other utilised methods [28], showing its potential. Though, there are a few applications of TOPSIS on real engineering application. Thus, it has been considered in energy market problem to explore its potential using heuristic methods.

In this work, double sided optimum bidding strategy for power suppliers and large buyers has been formulated with amalgamation of substantial wind and solar based power generation. This problem has been solved as multi-objectives using TOPSIS with a novel heuristic technique, Gravitational Search Algorithm (GSA) [30], which is one of the latest nature-inspired algorithm. GSA is well established and capable of solving optimisation problems [31–34]. It is inspired by the gravity law and the motion principle. This algorithm is classified by population-based approach consisting of different masses. The masses are sharing information based on the gravitational force to guide the search to the best location in the search space. Compared to bio-inspired or other nature-inspired algorithms such as GA, PSO and so on [17, 30], this algorithm based on the laws of physics tends to show better characteristics. Further, wind and solar are used as probabilistic manner to model the uncertainty and their prediction errors are considered in cost function using underestimation and overestimation.

2 Modelling of renewable power sources

In this section, modelling of solar irradiation and wind speed is elaborated. Solar irradiation is modelled using beta probability density function (pdf) and wind speed is modelled through Weibull pdf. The power probability distributions obtained from respective models are used in further simulations.

2.1 Modelling of wind power

The uncertainty of wind speed is generally being modelled by using a two parametric function, Weibull distribution [35]. It is defined as follows:

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

where k and c are shape factor and scale factor and v is wind speed in m/s. The values of k and c are approximately calculated using a known mean of historical wind speed (μ_{hws}) and standard deviation (σ_{std}) as follows:

$$k = \left(\frac{\sigma_{std}}{\mu_{hws}}\right)^{(-1.086)} \quad (2)$$

$$c = \left(\frac{\mu_{hws}}{\Gamma(1 + (1/k))}\right) \quad (3)$$

Different scenarios are generated from the wind speed data obtained from anemometers which measures the speed at different height in wind farms. To mimic the same patterns, firstly, 1000 scenarios are generated randomly by using Weibull distribution which are further converted into power scenarios corresponding to

desirable hub heights. In some situations, hub heights and anemometers heights are not same. In such cases wind speed is expressed as [36]

$$v(h_{est}) = v(h_{rkh}) \left(\frac{h_g}{h_{kah}}\right)^\gamma \quad (4)$$

where $v(h_{est})$ and $v(h_{rkh})$ are calculated wind speed at wind turbine's hub for power generation and the recorded wind speed at known hub height in (m/s), respectively; h_g is the hub height of wind turbine generator (m); h_{kah} is height of located anemometer; and γ is the parameter of shear coefficient, which governed by surface roughness and atmosphere condition. The calculated wind speeds are transformed into wind power using power curve of wind turbine. The power curve represents relation between wind speed and wind power. This correlation can be written as [36]

$$W_a(v) = \begin{cases} 0, & v \leq v_{in} \\ \frac{1}{2} \eta_p(v) \rho A_s v^3, & v_{in} \leq v \leq v_r \\ W_r, & v_r \leq v \leq v_o \\ 0, & v \geq v_o \end{cases} \quad (5)$$

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

The obtained wind power variable can be fitted into distribution using power curve to estimate the probability of wind power in different operating zones.

The probability of the linear part of wind power output can be written as

$$f_w(v_{in} \leq v \leq v_r) = \left(\frac{kz v_{in}}{c W_r}\right) \left[\frac{(1 + z W_a/W_r) v_{in}}{c}\right] \times \left\{ - \left[\frac{(1 + z W_a/W_r) v_{in}}{c}\right]^k \right\} \quad (6)$$

here, $z = ((v_r - v_{in}))/v_{in}$

The probability of zero wind power output can be expressed as

$$f_w[(v \leq v_{in}) \quad \& \quad (v \geq v_o)] = 1 - \exp\left[-\left(\frac{v_{in}}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \quad (7)$$

The probability of maximum (rated) wind power output can be written as

$$f_w(v_r \leq v \leq v_o) = \exp\left[-\left(\frac{v_r}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \quad (8)$$

2.2 Modelling of solar power

Solar irradiation usually depends on the temperature of the solar cell, solar insolation and the technical properties of various solar module. The output of solar power can be calculated by using solar irradiance and temperature, which can be expressed as [35]

$$T_{cell,t} = T_a + S_{i,t} \left(\frac{T_{NO} - 20}{0.8}\right) \quad (9)$$

$$I_t = S_{i,t} [I_{sc} + I_{TK}(T_{cell,t} - 25)] \quad (10)$$

$$V_t = V_{oc} - V_{TK} \times T_{cell,t} \quad (11)$$

$$S_{PO,t}(S_{i,t}) = n \times I_t \times V_t \times FF \quad (12)$$

here

$$FF = \frac{I_{mpp} \times V_{mpp}}{I_{sc} \times V_{oc}} \quad (13)$$

The irradiance of solar exist partial predictability because of known sun oriented introduction and of restricted hour accessibility. In this work, data for solar irradiations is considered of Barnstable city, Massachusetts, USA. It is observed that this data follow a beta probability distribution which can be expressed as [37]

$$B_{pdf}(S_{i,t}) = \left\{ \begin{aligned} & \frac{\Gamma(A_t + B_t)}{\Gamma(A_t)\Gamma(B_t)} \times \left(\frac{S_{i,t}}{S_{i,max,t}} \right)^{(A_t-1)} \\ & \times \left(1 - \frac{S_{i,t}}{S_{i,max,t}} \right)^{(B_t-1)} \end{aligned} \right\}, \quad (14)$$

$$0 \leq \left(\frac{S_{i,t}}{S_{i,max,t}} \right) \leq 1, \quad A_t > 0, \quad B_t > 0$$

The value of beta distribution parameters (A_t, B_t) calculated by utilising the mean (μ_{si}) and standard deviation (σ_{si}) of historical solar irradiation's data is as follows:

$$A_t = \mu_{si}^2 \left(\frac{1 - \mu_{si}}{\sigma_{si}} - \frac{1}{\mu_{si}} \right) \quad (15)$$

$$B_t = A_t \left(\frac{1}{\mu_{si}} - 1 \right) \quad (16)$$

Meanwhile, the variables of beta distribution lie in the interval range of (0, 1). Thus, a nominal value of solar irradiation is ($S_{i,t}/S_{i,max,t}$) considered. Therefore, 1000 scenarios are generated randomly by using beta distribution which is further converted into power scenarios corresponding to desirable PV module. The solar pdf also follows the beta distribution model [37]

$$B_{pdf}(S_{PV,t}) = \left\{ \begin{aligned} & \frac{1}{S_{PV,t}^{max}} \times \frac{\Gamma(A_t + B_t)}{\Gamma(A_t)\Gamma(B_t)} \times \left(\frac{S_{PV,t}}{S_{PV,t}^{max}} \right)^{(A_t-1)} \\ & \times \left(1 - \frac{S_{PV,t}}{S_{PV,t}^{max}} \right)^{(B_t-1)} \end{aligned} \right\}, \quad (17)$$

$$0 \leq \left(\frac{S_{PV,t}}{S_{PV,t}^{max}} \right) \leq 1, \quad A_t > 0, \quad B_t > 0$$

2.3 Wind and solar power scenarios reduction

One Thousand (1000) scenarios of solar and wind are generated. However, probability of few scenarios might be very small and in some cases probabilities may be same. Subsequently, it is important to scrutinise the scenarios to obtain significant fewer scenarios while remaining lower and equal probability scenarios. The reduction should be such that the stochastic properties do not change. The amount of scenarios decreased depends on the type and nature of the problem to be optimised and must be reduced to or less than one-fourth of generated scenarios [36]. In this, a scenario reduction technique known as Kantorovich distance matrix (KDM) [38] has been employed. It is based on the Euclidian distance between scenarios and their corresponding probabilities. This reduced the scenarios with closest and low probabilities. These are the following steps used to compute KDM.

Step 1: Calculate the Euclidian distance for each scenario to all other scenarios. The distance between any two scenarios v^i and v^j is given by

$$KD(v^i, v^j) = \left(\sum_{l=0}^m (v_l^i - v_l^j)^2 \right)^{1/2} \quad (18)$$

Step 2: Find the minimum closest distance $\min \{KD(v^i, v^j)\}$ for every scenario v^i to the scenario $v^j, j \neq i$.

Step 3: Multiply distance obtained in step 2 with their corresponding probability

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

Step 4: Eliminate the scenario with minimum distance and low probability. Subsequently, add eliminated scenario's probability to the next nearest scenario.

Step 5: Repeat steps 2–4 to until the stopping criterion is reached.

2.4 Assessment of scheduled wind and solar powers amount for bidding

The planned wind (W_g) and solar (S_g) power is obtained using KDM and the appropriate probabilities are calculated as follows:

$$W_g = \sum_{i=1}^{n_i} W_{ai} \times \text{prob}_i \quad (20)$$

$$S_g = \sum_{i=1}^{n_i} S_{ai} \times \text{prob}_i \quad (21)$$

here, prob_i is corresponding probability of reduced i th wind and solar power scenario, respectively.

2.5 Wind and solar power cost evaluation

The wind and solar power are inherently uncertain in nature which always results in deviation in day-ahead forecast and actual power generation. Therefore, there is persistently underestimation (actual power is more than forecasted power) and overestimation (actual power is less than forecasted power) of wind power. This condition of mismatch can be incorporated as an imbalance term in cost function in the case of when wind and solar generation are owned by the system operator. This imbalance cost of wind and solar can be measured by difference in forecasted and actual power which is summation of underestimation and underestimation cost [35]. It can be expressed as

$$IMC(W_{g_n}) = O_c(w_g) + U_c(w_g) \quad (22)$$

$$IMC(S_{g_n}) = O_c(S_g) + U_c(S_g) \quad (23)$$

where $O_c(w_g)$ and $O_c(S_g)$ represent the overestimation cost, $U_c(w_g)$ and $U_c(S_g)$ represent the cost of underestimation for available wind and solar energy, respectively.

The assessment of overestimation and underestimation cost of the solar and wind energy available is as follows.

2.5.1 Assessment of overestimation cost for available wind and solar power:

The deficit in power is a decisive factor in evaluating the cost of overestimation of solar and wind power and the probability of the incidence of shortage for a specified amount of scheduled solar and wind power. Thus, it can be formulated as [35]

$$O_c(w_g) = K_o * \int_0^{W_g} (W_g - W_a) * f_{W_a}(W_a) * dW_a \quad (24)$$

$$O_c(S_g) = K_o * \int_0^{S_g} (S_g - S_a) * f_{S_a}(S_a) * dS_a \quad (25)$$

where K_o is the penalty cost for reserve power purchases per \$/kWh due to overestimation of solar and wind power.

2.5.2 Assessment of underestimation cost for available solar and wind power:

The cost of underestimation depends on measure of actual solar and wind generation which is in surplus

and the probability of occurrence of excess power. Therefore it does not indicate true cost rather it represents penalty term for wastage of available resources [35]

$$U_c(W_g) = K_u * \int_{W_g}^{W_{max}} (W_a - W_g) * f_{W_a}(W_a) * dW_a \quad (26)$$

$$U_c(S_g) = K_u * \int_{S_g}^{S_{max}} (S_a - S_g) * f_{S_a}(S_a) * dS_a \quad (27)$$

where K_u is the penalty for situational loss of profit per \$/kWh due to underestimation of solar and wind power.

3 Formulation of problem for double sided strategic bidding of power suppliers and large buyers with wind and solar power

Assume a system, where sealed bid and evenly distributed MCP is organised, consists u independent suppliers, a market operator, and aggregated forecasted load elastic with the cost of electricity, z big buyers who are involved in the demand side bidding. Suppose individual supplier/big buyers are required to offer the market operator, respectively, represented by a linear non-decreasing supply/non-increasing demand function

$$C_n(P_n) = \alpha_n + \beta_n P_n, \quad n = 1, 2, \dots, u \quad (28)$$

$$L_m(D_m) = \theta_m - \pi_m D_m, \quad m = 1, 2, \dots, z \quad (29)$$

where P_n is active power generation, D_m is the active power load, $\alpha_n, \beta_n, \theta_m, \pi_m$ are bidding coefficients which must be non-negative. Now the market operator decides a set of generation/demand that meets and minimises total buying cost and maximises social welfare by solving the following equations:

$$\alpha_n + \beta_n P_n = MCP \quad (30)$$

$$\theta_m - \pi_m D_m = MCP \quad (31)$$

$$\sum_{n=1}^u P_n + \sum_{n=1}^{wg} Wg_n + \sum_{n=1}^{sg} Sg_n = Q(MCP) + \sum_{m=1}^z D_m \quad (32)$$

$$P_{min,n} \leq P_n \leq P_{max,n} \quad (33)$$

$$D_{min,m} \leq D_m \leq D_{max,m} \quad (34)$$

where $P_{min,n}$ and $P_{max,n}$ are lower and upper limits of the active power output for n th supplier, respectively. $D_{min,m}$ and $D_{max,m}$ are lower and upper limits of the demand for m th buyer, respectively. $Q(MCP)$ is forecasted load by the pool. Assume $Q(MCP) = Q_c - k * MCP$

$$Q(MCP) = Q_c - k * MCP \quad (35)$$

where Q_c is constant and $k = 5$ is load price elasticity that is non-negative. The solution of (30)–(32) when (33), (34) are ignored is

$$MCP = \frac{Q_c - \sum_{n=1}^{wg} Wg_n - \sum_{n=1}^{sg} Sg_n + \sum_{n=1}^u \frac{\alpha_n}{\beta_n} + \sum_{m=1}^z \frac{\theta_m}{\pi_m}}{k + \sum_{n=1}^u \frac{1}{\beta_n} + \sum_{m=1}^z \frac{1}{\pi_m}} \quad (36)$$

$$P_n = \frac{MCP - \alpha_n}{\beta_n} \quad (37)$$

$$D_m = \frac{\theta_m - MCP}{\pi_m} \quad (38)$$

If the solution of P_n in (37) exceed its maximum limits, P_n is set to $P_{max,n}$. If $P_n < P_{max,n}$, P_n is set to zero. A similar procedure is used for D_m .

For building strategic bidding profit/benefit maximisation of supplier/buyer can be defined as

$$\text{Maximise: } \begin{aligned} & F(\alpha_n, \beta_n) = MCP \times (P_n + Wg_n + Sg_n) \\ & - C_n(P_n) - IMC(Wg_n) - IMC(Sg_n) \end{aligned} \quad (39)$$

$$\text{Maximise: } F(\theta_m, \pi_m) = B_m(D_m) - MCP * D_m \quad (40)$$

Subject to: (20)–(23) and (36)–(38)

where $C_n(P_n) = a_n P_n + b_n P_n^2$ is production cost function of the suppliers, $B_m(D_m) = e_m D_m - f_m D_m^2$ is buyers cost function, and $(a_n, b_n) / (e_m, f_m)$ are cost coefficients of the suppliers/buyers. Supplier/buyers aim to determine $\alpha_n, \theta_m, \beta_n, \pi_m$ to maximise (39)/(40) subject to (20)–(23) and (36)–(38).

Bidding data for next duration is confidential in a sealed bid competitive electricity market. Therefore, participants do not have information about other participant's bid. However, last duration bidding data information is available, based on this data estimation of MCP is possible. Each participant tries to estimate other participants bidding coefficients, but this is difficult. So, from each participant's point of view, a normal joint distribution with following pdf follows the bidding coefficient. pdf for every supplier is

$$pdf_i(\alpha_n, \beta_n) = \frac{1}{2\pi\sigma_n^{(\alpha)}\sigma_n^{(\beta)}\sqrt{1-\rho_n^2}} \times \exp\left\{-\frac{1}{2(1-\rho_n^2)}\left[\left(\frac{\alpha_n - \mu_n^{(\alpha)}}{\sigma_n^{(\alpha)}}\right)^2 + \left(\frac{\beta_n - \mu_n^{(\beta)}}{\sigma_n^{(\beta)}}\right)^2 - 2\rho_n\left(\frac{\alpha_n - \mu_n^{(\alpha)}}{\sigma_n^{(\alpha)}}\right)\left(\frac{\beta_n - \mu_n^{(\beta)}}{\sigma_n^{(\beta)}}\right)\right]\right\} \quad (41)$$

This pdf can be indicated in the compressed form

$$(\alpha_n, \beta_n) \sim N\left\{\begin{bmatrix} \mu_n^{(\alpha)} \\ \mu_n^{(\beta)} \end{bmatrix}, \begin{bmatrix} (\sigma_n^{(\alpha)})^2 & \rho_n \sigma_n^{(\alpha)} \sigma_n^{(\beta)} \\ \rho_n \sigma_n^{(\alpha)} \sigma_n^{(\beta)} & (\sigma_n^{(\beta)})^2 \end{bmatrix}\right\} \quad (42)$$

where ρ_n is correlation coefficient between α_n and β_n , parameters of the combined distribution is $\mu_n^{(\alpha)}, \mu_n^{(\beta)}, \sigma_n^{(\alpha)}$ and $\sigma_n^{(\beta)}$. The marginal distributions of α_n and β_n are both normal with mean values of $\mu_n^{(\alpha)}$ and $\mu_n^{(\beta)}$, and standard deviations $\sigma_n^{(\alpha)}$ and $\sigma_n^{(\beta)}$, respectively. Similarly, for each large buyer, the assumed pdf is

$$(\theta_m, \pi_m) \sim N\left\{\begin{bmatrix} \mu_m^{(\theta)} \\ \mu_m^{(\pi)} \end{bmatrix}, \begin{bmatrix} (\sigma_m^{(\theta)})^2 & \rho_m \sigma_m^{(\theta)} \sigma_m^{(\pi)} \\ \rho_m \sigma_m^{(\theta)} \sigma_m^{(\pi)} & (\sigma_m^{(\pi)})^2 \end{bmatrix}\right\} \quad (43)$$

The meaning of $\mu_m^{(\theta)}, \mu_m^{(\pi)}, \sigma_m^{(\theta)}, \sigma_m^{(\pi)}$ and ρ_m are similar to $\mu_n^{(\alpha)}, \mu_n^{(\beta)}, \sigma_n^{(\alpha)}, \sigma_n^{(\beta)}$ and ρ_n .

Depending on the last bidding hour data, it is possible to determine these distributions [23]. Function for joint distribution of $\alpha_n, \beta_n, \theta_m$ and π_m is represented by distribution of probability, with the objective functions (39) / (40) subject to equations (20)–(23) and (36)–(38) are stochastic optimisation problem.

4 Multi-objective problem formulation using TOPSIS technique

All objectives of bidding problem can be represented as Maximise

$$[O_1(x), O_2(x), \dots, O_{n_2}(x)] \quad (44)$$

Subjected to: $x \in S$

where $O_i(x): R^n \rightarrow R$ is i th objective, $i = 1, 2, \dots, n_2, n_2 > 1$ and S is space of the search.

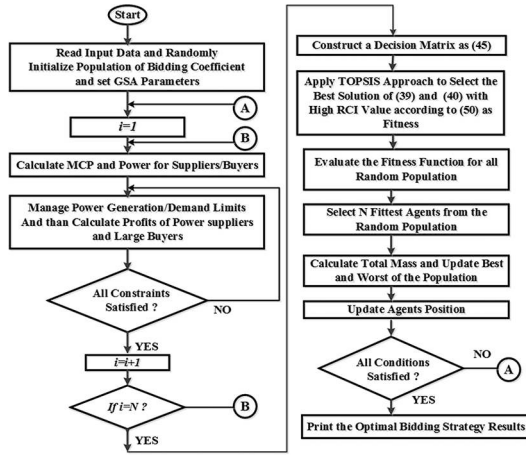


Fig. 1 Flow chart for TOPSIS with GSA (TGSA)

As mentioned, TOPSIS technique is implemented to frame and solve the multi-objective double sided strategic bidding problem for profit maximisation of the suppliers and large buyers. In this technique, Euclidean geometry is applied, and two reference points like positive ideal solutions (PIS) and negative ideal solutions (NIS) are used to find best compromising result. Therefore, choice of the alternative result should be at nearest Euclidean distance from PIS and farthest from NIS. Using this procedure, the solutions remain focused on their own best solution. This result increases high-quality of results for actual multi-objective optimisation problems.

In TOPSIS technique, following steps are used to solve a multi-objective problem

4.1 Step I

Frame a standardised selection matrix to transform all dimensional functions into non-dimensional functions. The factors of matrix may be represented by

$$F_{ab} = \frac{O_{ab}}{\sqrt{\sum_{a=1}^{n_1} O_{ab}^2}}, \quad \forall a \in n_1 \text{ \& } b \in n_2 \quad (45)$$

where n_1 is the number of elements and F_{ab} is the value of a th element of b th objective.

4.2 Step II

A standardised weighted selection matrix may be constructed to provide the objects with weights if necessary. If all objects are similarly significant, the step can be avoided. The matrix factors are represented by

$$W_{ab} = w_b \times F_{ab}, \quad \forall a \in n_1 \text{ \& } b \in n_2 \quad (46)$$

where w_b is weight of the b th objective and $\sum_{b=1}^{n_2} w_b = 1$.

4.3 Step III

To maintain the best and worst solutions of each objective, PIS and NIS are calculated and expressed as

$$\text{PIS} = \{W_1^+, W_2^+, W_3^+, \dots, W_{n_2}^+\} \quad (47)$$

$$\text{NIS} = \{W_1^-, W_2^-, W_3^-, \dots, W_{n_2}^-\} \quad (48)$$

where

$$W_b^+ = \begin{cases} \max \langle W_{ab} \rangle, & \forall a; \text{ if object denotes a profit} \\ \min \langle W_{ab} \rangle, & \forall a; \text{ if object denotes a benefit} \end{cases}$$

$$W_b^- = \begin{cases} \max \langle W_{ab} \rangle, & \forall a; \text{ if object denotes a benefit} \\ \min \langle W_{ab} \rangle, & \forall a; \text{ if object denotes a profit} \end{cases}$$

4.4 Step IV

For every opportunity from PIS and NIS, Euclidean distances d_{b+} and d_{b-} are measured and given by

$$d_a^+ = \sqrt{\sum_{b=1}^{n_2} (W_{ab} - W_b^+)^2} \quad \& \quad d_a^- = \sqrt{\sum_{b=1}^{n_2} (W_{ab} - W_b^-)^2} \quad (49)$$

4.5 Step V

The relative closeness index (RCI) can be measured for individual opportunity using the value from step 4

$$\text{RCI}_a^+ = \frac{d_a^-}{d_a^+ + d_a^-} \quad (50)$$

The best compromising results may be selected from RCI. The alternatives having highest RCI value will be selected as the best compromising result.

GSA is used to solve the above stochastic optimisation problem, and is presented in the next section.

5 Gravitational search algorithm

In [30], authors proposed a GSA to solve the problems of non-differentiable and non-linear optimisation. Every agent in GSA provides a better solution to the problem. The flowchart solution procedure is given in Fig. 1.

5.1 Initialisation of population

Assume a system consisting of N agents (masses) representing the position of the k th agent

$$\lambda_k = (\lambda_k^1, \dots, \lambda_k^D, \dots, \lambda_k^M) \quad \text{for } k = 1, 2, \dots, N \quad (51)$$

where $\lambda_k^D \in [L_k^D, U_k^D]$, $D = 1, 2, \dots, M$, is the k th agent position in the D th dimension and M is the dimension of search space and L_k^D , U_k^D are lower bound and upper bound limits of k th agents in the D th dimension.

5.2 Evaluation of fitness

Here the best solution of (39) and (40) is considered according to (50) as fitness function fit_k .

5.3 Acceleration of agents

The evaluation of fitness is used to calculate each agent's weight in GSA. Each agent's mass is calculated as follows:

$$\begin{cases} M_k(i) = \frac{m_k(i)}{\sum_{l=1}^N m_l(i)} \\ m_k(i) = \frac{fit_k(i) - \text{worst}(i)}{\text{best}(i) - \text{worst}(i)} \end{cases} \quad (52)$$

where $M_k(i)$ is the normalised mass of k th agent at i th iteration and $\text{worst}(i)$, $\text{best}(i)$ are the worst and best fitness of all agents at i th iteration. The acceleration $a_k^D(i)$ acting on k th agent at iteration i is evaluated follows:

$$a_k^D(i) = \sum_{l \in G_{\text{best}} \atop l \neq k} \text{rand}_l G(i) \frac{M_k(i)}{R_{kl}(i) + E} (\lambda_l^D(i) - \lambda_k^D(i)) \quad (53)$$

where the set of first 2% agents has the best fitness value G_{best} and the highest weights $rand_l$ is the uniform random number between interval (0, 1). $R_{kl}(i)$ is the Euclidean distance between two agents k th and l th at i th iteration and E is a small positive constant. The gravitational function $G(j)$ is represented by

$$\begin{cases} G(i) = G \times \left(1 - \frac{\text{iteration}}{\text{Total iteration}}\right) \\ G = c \max_{D \in \{1, 2, \dots, M\}} (\lambda_U^D - \lambda_L^D) \end{cases} \quad (54)$$

where c is search interval parameter.

5.4 Update the position and agents velocity

The next iteration ($i + 1$)th calculates the position and the velocity of the agents as follows:

$$\begin{cases} v_k^D(i+1) = rand_k \times v_k^D(i) + a_k^D(i) \\ \lambda_k^D(i+1) = \lambda_k^D(i) + v_k^D(i+1) \end{cases} \quad (55)$$

where $rand_k$ is a random number between interval (0, 1), $v_k^D(i)$ is the velocity of k th agent at D th dimension during i th iteration and $\lambda_k^D(i)$ is the position of k th agent at D th dimension during i th iteration.

5.5 Pseudo-code of TGSA for double sided bidding strategy

1. Agent's Initialisation
 - a. Initial population for bidding coefficients β_n/π_m are randomly generated in the interval between b_n/f_m and $M*b_n/M*f_m$ and M is set to be 10.
 - b. Read input data (parameters of joint pdf, suppliers and large buyer's data, GSA parameters and maximum iterations).
2. Estimate optimal bidding coefficients using (42) and (43). Thereafter determine the MCP and power dispatch for suppliers and large buyers.
3. If power dispatch limits of suppliers and large buyers is violated. It is set according to equations (33) and (34), respectively.
4. Calculate profits and benefits for each power suppliers and buyers.
5. The fitness as (50) is calculated and then for each agent's worst and best values of fitness is estimated as follows:

$$\text{worst}(t) = \min_{j \in \{1 \dots N\}} \text{fit}_j(t) \quad (56)$$

$$\text{best}(t) = \max_{j \in \{1 \dots N\}} \text{fit}_j(t) \quad (57)$$

6. Determine the value of gravitational constant (G) by utilising (54)
7. Evaluate each agent's mass and acceleration for iterations by utilising (52) and (53), respectively.
8. Update the velocity and position of agent's by utilising (55).
9. Repeat from 6 to 8 until iteration has reached its maximum number. Report the best fitness calculated as global fitness at the final iteration (maximum profit/benefit).

6 Result and discussion

In this section, the proposed double sided optimal strategic bidding model is analytically tested on IEEE 30-bus [23] and 57-bus [17] systems, respectively, and the system data for suppliers and large buyers is presented in Table 1. The systems consist of six and seven conventional power suppliers (CPS), respectively, and two large and 1500 MW with load price elasticity ($k=5$) at the time of

Table 1 Suppliers and large buyers data for both systems (IEEE 30-bus and 57-bus systems)

Systems	Generator	a	b	P_{\min} , MW	P_{\max} , MW
IEEE 30-bus system	1	6.0	0.01125	40	160
	2	5.25	0.0525	30	130
	3	3.0	0.1375	20	90
	4	9.75	0.02532	20	120
	5	9.0	0.075	20	100
	6	9.0	0.075	20	100
IEEE 57-bus system	1	1.7365	0.0017	50	576
	2	10.0	0.0100	10	100
	3	7.1429	0.0071	20	140
	4	10.0	0.0100	10	100
	5	1.81	0.0018	40	550
	6	10.0	0.0100	10	100
	7	2.4390	0.0024	30	410
Buyers	e	f	D_{\min} , MW	D_{\max} , MW	
large buyers	1	30	0.04	00	200
	2	25	0.03	00	150

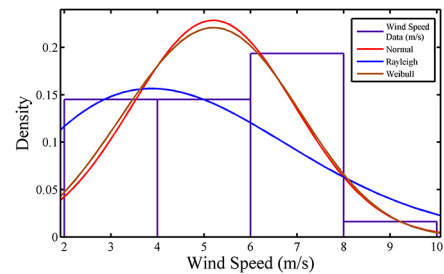


Fig. 2 Wind speed data is fitted into various probability distributions

Table 2 Log likelihood, mean and variance values for various distributions of historical wind speed data

	Normal fit	Rayleigh fit	Weibull fit
log likelihood value	-60.742	-65.6732	-60.4794
mean	5.20054	4.85338	5.20428
variance	3.04414	6.43624	2.99978

bidding for IEEE 30-bus and 57-bus systems, respectively. The proposed framework is utilised to obtain the maximum profit for power suppliers and large buyers. First, the test is conducted and analysed on this system. Further, the considered model is modified to accommodate one solar and one wind power supplier to the extent the influence of solar and wind source. In this work, one supplier of wind and solar of each rated capacity of 200 MW are considered. The proposed model has been framed as a multi-objective optimisation problem and solved by using TOPSIS amalgamation with GSA (TGSA) in MATLAB R2014a on a 3.20 GHz, i5 processor, 4 GB RAM PC.

For the wind power estimation, single hour wind speed data from 1 August to 31 August 2005 of Barnstable city, Massachusetts, USA is taken from [39]. The air density and shear coefficient value are 1.242 kg/m^3 and 0.35, respectively. The wind turbine VENSYS-100 [40] and 2.5 MW capacity generator located at 100 m hub height are used to generate wind power. The wind speed data is fitted into various probability distributions are shown in Fig. 2.

The values of log likelihood, mean and variance are calculated using various distributions and are presented in Table 2. It should be noted that the log-likelihood value of Weibull distribution is better than others, indicating best fitting of the data in the distribution.

The values of shape and scale parameters calculated using (2) and (3) are 3.3094 and 8.0654 m/s, respectively. Then, thousand wind speed scenarios are generated and converted into power scenarios using wind speed-power relationship. A normalisation

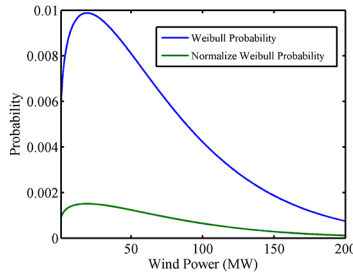


Fig. 3 Weibull and normalise probabilities density function for generated power scenarios

Table 3 PV module specifications

Characteristics of module	Unit
PV^{\max} (peak of output)	340 W
I_{TK}	0.047 mA/°C
V_{TK}	0.335 mV/°C
FF (fill factor)	0.755
T_a (ambient temperature)	25°C
T_{NO} (nominal cell operating temperature)	46°C
I_{mpp} (current at maximum power)	8.99 A
V_{mpp} (voltage at maximum power)	37.8 V
V_{oc} (open circuit voltage)	46 V
I_{sc} (short circuit current)	9.78 A

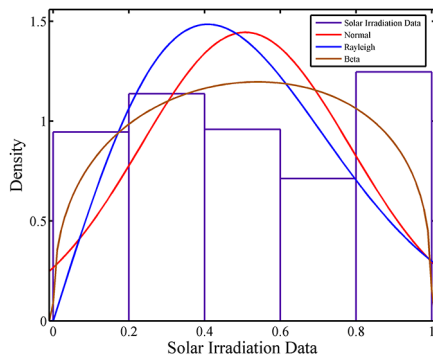


Fig. 4 Historical solar irradiation data is fitted into various probability distributions

Table 4 Log likelihood, mean and variance values for various distributions of historical solar irradiation data

	Normal fit	Rayleigh fit	Beta fit
log likelihood value	-47.6376	-33.1864	10.1381
mean	0.507468	0.51182	0.510256
variance	0.0762217	0.0715777	0.0677011

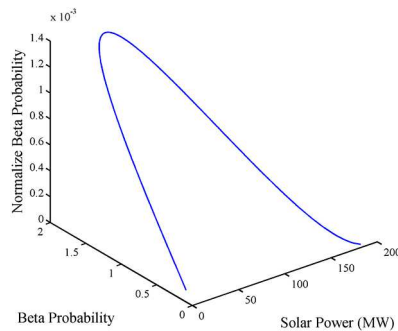


Fig. 5 Beta and normalise probabilities density function for generated power

probability obtained using Weibull distribution is assigned to each generated scenario so that their summation becomes equal to unity. The Weibull and normalise density function of probabilities are shown in Fig. 3 for generated power scenarios.

For the solar power estimation, single hour solar irradiation data from 1 January to 31 December 2013 of Barnstable city, Massachusetts, USA is taken from [41]. Solar irradiation is converted into solar power by using PV module specifications taken from [35] and given in Table 3. The solar irradiation data fitted into various probability distributions are shown in Fig. 4.

The values of log likelihood, mean and variance are calculated using various distributions and are presented in Table 4. It should be noted that the log-likelihood value of beta distribution is better than others, indicating best fitting of the data in the distribution.

The values of beta distribution parameters A and B are 1.3732 and 1.3180, respectively, for historical solar irradiation data and calculated by using (15) and (16) respectively. Then, a thousand solar irradiation scenarios are generated and converted into power scenarios using PV module specifications. A normalisation probability obtained using beta distribution is assigned to each generated scenario so that their summation becomes equal to unity. The beta and normalise density function of probabilities is shown in Fig. 5 for generated power scenarios.

Since, the large number of scenarios predicts the uncertainty of wind and solar power. However, there are few scenarios exhibiting the same assessment. Therefore, KDM [36] method is employed to eliminate such scenario for better modelling of wind power. Here, 10 reduced scenarios generated using 1000 scenarios for wind and solar are given in Table 5. Based on the final obtained value of wind and solar power outputs and their corresponding probabilities, the expected values of wind and solar power are 50.31 and 70.76 MW, respectively.

In the light of discussion in introduction section, authors concluded that the behaviour of both entities power suppliers and large buyers are contradictory. Thus, it becomes important for an algorithm to identify the overall optimal operating point considering both entities (suppliers and buyers) together. Therefore, first, the optimal double sided strategic bidding model is framed as a multi-objective optimisation problem and then solved by using TGSA. Thereafter, modified test systems are considered with wind power only, with solar only and with combined wind-solar.

IEEE-30 bus system has been already investigated in strategic bidding problem considering suppliers and buyers in [23]. Therefore, the proposed formulation has been firstly tested on IEEE-30 bus system and compared with Monte Carlo (MC) [23]. In the proposed methodology, the bidding coefficients are not considered individually for profit maximisation of both entities power suppliers and large consumers. Since bidding coefficients show inter-dependency, here the value of one bidding coefficient is taken as fixed so as to determine the other coefficients by employing an optimisation technique [23]. In this article, bidding coefficient α_n/θ_m is taken as fixed where β_n/π_m are determined by using TGSA by considering search space between b_n/f_m and $M*b_n/M*f_m$ and also value of M is taken as 10 [23]. For suppliers and buyers the values of joint normal distribution parameters are obtained from [23] as shown in (42) and (43), respectively. The optimal double sided strategic bidding to clear the MCP for IEEE 30 bus system is evaluated with the help of bidding coefficients predicated by the TGSA and their corresponding profits and individual dispatch of generators are measured. The optimal double sided strategic bidding results for IEEE 30 bus system using MC [23] and proposed TGSA are given in Table 6.

It is observed from Table 6 that the overall profit of suppliers is increased using TGSA as compared to MC [23] by \$ 60.7. Also, the overall benefit of buyers using TGSA is increased as compared to MC [23] by \$ 9.2. TGSA provides an optimal MCP that maximises the profit/benefit of suppliers/buyers. Thus, it further encourages both entities to increase the trade of power. It is also observed from Table 6 that TGSA results in 22.8 MW more power traded than MC [23]. The value of objective functions summation considering double sided bidding using TGSA is increased as compared to MC [23] by \$ 69.9. Results for the IEEE 30-bus

Table 5 Final KDM of reduced ten numbers of scenarios for wind and solar power

System	Index	1	2	3	4	5	6	7	8	9	10	Output	Prob.	Min, KD
wind	1	0	17.39	45.38	63.97	79.87	97.11	121.5	136.3	150.2	165.5	29.22	0.546236	17.39
	2	17.39	0	27.99	46.58	62.48	79.72	104.1	118.9	132.8	148.1	46.62	0.181994	17.39
	3	45.38	27.99	0	18.59	34.49	51.73	76.12	90.90	104.8	120.1	74.61	0.105963	18.59
	4	63.97	46.58	18.59	0	15.9	33.14	57.53	72.31	86.24	101.5	93.2	0.087006	15.9
	5	79.87	62.48	34.49	15.9	0	17.24	41.63	56.41	70.34	85.62	109.1	0.037677	15.9
	6	97.11	79.72	51.73	33.14	17.24	0	24.39	39.17	53.1	68.38	126.3	0.026649	17.24
	7	121.5	104.1	76.12	57.53	41.63	24.39	0	14.78	28.71	43.99	150.7	0.004927	14.78
	8	136.3	118.9	90.9	72.31	56.41	39.17	14.78	0	13.93	29.21	165.5	0.006487	13.93
	9	150.2	132.8	104.8	86.24	70.34	53.1	28.71	13.93	0	15.28	179.4	0.002440	13.93
	10	165.5	148.1	120.1	101.5	85.62	68.38	43.99	29.21	15.28	0	194.7	0.000622	15.28
solar	1	0	14.01	41.31	65.74	82.84	99.31	109.9	127.2	138.5	154	12.44	0.009583	14.01
	2	14.01	0	27.3	51.73	68.83	85.29	95.89	113.21	124.5	140	26.46	0.067130	14.01
	3	41.31	27.3	0	24.43	41.54	58	68.59	85.91	97.17	112.71	53.75	0.450183	24.43
	4	65.74	51.73	24.43	0	17.11	33.57	44.16	61.48	72.74	88.28	78.18	0.208449	17.11
	5	82.84	68.83	41.54	17.11	0	16.46	27.06	44.38	55.63	71.17	95.29	0.130413	16.46
	6	99.31	85.29	58	33.57	16.46	0	10.59	27.91	39.17	54.71	111.7	0.082165	10.59
	7	109.9	95.89	68.59	44.16	27.06	10.59	0	17.32	28.58	44.11	122.3	0.032668	10.59
	8	127.2	113.2	85.91	61.48	44.38	27.91	17.32	0	11.26	26.80	139.7	0.015613	11.26
	9	138.5	124.5	97.17	72.74	55.63	39.17	28.58	11.26	0	15.54	150.9	0.003062	11.26
	10	154	140	112.7	88.28	71.17	54.71	44.11	26.80	15.54	0	166.5	0.000735	15.54

Table 6 Optimal bidding result for IEEE 30-bus system using MC [23] and TGSA

Suppliers	α_n	MC [23]			Proposed TGSA		
		β_n	P, MW	Profit, \$	β_n	P, MW	Profit, \$
1	6.0	0.02927	160	1368	0.037574	160	1386.6
2	5.25	0.12420	89.4	572.7	0.119268	114.2	596.2
3	3.0	0.29231	45.7	322.9	0.449634	50.09	329.52
4	9.75	0.07433	88.8	386.4	0.098465	88.35	395.73
5	9.0	0.17058	43.1	177.5	0.673058	40.15	178.85
6	9.0	0.17058	43.1	177.5	0.673058	40.15	178.85
total			470.1	3005		492.9	3065.7
Buyers	θ_m	π_m	D, Benefit, MW \$		π_m , D, Benefit, MW \$		
			D, MW	Benefit, \$	D, MW	Benefit, \$	
1	30	0.09771	139.7	1126.3	0.090492	149.6	1129.4
2	25	0.07719	112.1	592.6	0.067894	125.7	598.7
total			251.8	1718.9		275.3	1728.1
MCP, \$/MW			16.35			16.47	
Q(MCP), MW			218.3			217.6	
total	power traded, MW		470.1			492.9	
total	(Profit + Benefit), \$			4723.9			4793.8

system show that the proposed technique in this paper is more suitable as compared to MC [23]. The obtained solutions are better may be due to the TGSA applied to find out the best compromising result. TOPSIS is fundamentally an effective method for multi-objective problem that decreases the Euclidean distance of Pareto-set from best result of individual objects and provides best compromising solution. Therefore, it is found that TGSA approach is effective and promising to obtain the most compromising solution for multi-objective strategic bidding problem of suppliers/ large buyers.

Renewable based power sources in the IEEE 30-bus system are successively considered to measure the effect of renewables. System operators are allowed to modify existing demand that means actual demand excluding generation from wind power for

strategic bidding of wind power on the emerging power market, system operator is permitted to modify the existing demand and then updating the coefficients of bidding in agreement with the modifying demand [11]. Based on this approach wind and solar power are considered to determine the new MCP. First the wind power generator is considered and new value of MCP is calculated by updating the bidding coefficients at modified demand. Similarly, MCP with the inclusion of solar power and finally, the aggregate benefits of wind and solar generator are considered. In this analysis, the consideration of operating cost for both the renewable sources has not been taken into account. However, due to the associated intermittency of these renewable sources it is acceptable to consider their imbalance cost. This cost is determined in terms of overestimation and underestimation of generation for both solar and wind. And the effect of this cost is reflected on the net profit obtained by renewable power suppliers in terms of revenue minus the imbalance cost. Also, the penalty coefficient and reserve coefficient linked with underestimation and overestimation separately are taken as 50% of MCP and equal to MCP, respectively [17]. The optimal double sided strategic bidding results on IEEE 30-bus test system with wind power only, IEEE 30-bus test system with solar power only and IEEE 30-bus test system with combined wind-solar power by using TGSA are given in Table 7.

From Table 6, it is observed that the market is cleared at MCP value of 16.47 \$/MW, total generation of CPS is 492.9 MW, total demand of large consumers is 275.3 MW, total power traded is 492.9 MW, and net profit for CPS and large consumers are \$ 3065.7 and \$ 1728.1, respectively. From Table 7, it is observed that when only wind power is included with CPS then MCP is reduced to 16.17 \$/MW, total generation of CPS is reduced to 483.98 MW, total demand of large consumers and total traded power are increased to 315.14 MW and 534.29, respectively, and the net profit of CPS is reduced to \$ 2842.14 which is caused by the lower value of MCP and generation of CPS. Moreover, the net profit of large consumers is increased significantly, which is caused by the lower value of MCP and higher demand of large consumers. The wind power net profit, overestimation and underestimation cost are \$290.55, \$58.21 and \$464.75, respectively. In the second case, i.e. only solar power with CPS, the net profit value, overestimation and underestimation cost are \$653.32, \$153.07 and \$327.18, respectively. For this case, the MCP value is 16.02 \$/MW, total generation of CPS 466.58 MW which is lower than conventional and wind due to significant power generation from the solar, total demand of large consumers and total traded power are increased to 317.44 MW and 537.34, respectively. Finally, when both the wind

Table 7 Optimal bidding result for IEEE 30-bus system with inclusion of only wind, only with solar, and combined both wind and solar using TGSA

Suppliers	α_n	Only with wind			Only with solar			Combined both with wind and solar		
		β_n	P , MW	Profit, \$	β_n	P , MW	Profit, \$	β_n	P , MW	Profit, \$
1	6.0	0.045911	160	1339.03	0.040742	160	1351.71	0.041573	160	1257.60
2	5.25	0.077421	130	532.21	0.595422	49.34	403.72	0.191982	56.42	420.21
3	3.0	0.976788	35.32	293.61	0.332060	58.56	291.12	0.167643	77.71	153.44
4	9.75	0.105655	76.08	341.79	0.047250	120	388.17	0.098310	62.31	269.95
5	9.0	0.276085	41.29	168.14	0.372599	39.34	160.21	0.175391	40.17	146.51
6	9.0	0.276085	41.29	168.14	0.372599	39.34	160.21	0.175391	40.17	146.51
Total			483.98	2842.14		466.58	2719.15		436.78	2394.22
Buyers	θ_m	π_m	D , MW	Benefit, \$	π_m	D , MW	Benefit, \$	π_m	D , MW	Benefit, \$
1	30	0.067565	200	1166.21	0.083473	167.46	1218.84	0.077034	186.15	1283.32
2	25	0.076698	115.14	619.09	0.057095	150	671.53	0.044185	150	725.10
total			315.14	1785.30		317.44	1890.36		336.15	2008.42
	MCP, \$/MW		16.17		16.02			15.66		
	Q(MCP), MW		219.16			219.88			221.70	
	total traded power, MW		534.29			537.34			557.85	
	renewable dispatch, MW		50.31			70.76			50.31 (W) 70.76 (S)	
	overestimation cost for renewables, \$			58.21			153.07			56.37 (W) 149.63(S)
	underestimation cost for renewables, \$			464.75			327.18			450.09 (W) 319.83 (S)
	imbalance cost for renewables, \$			522.96			480.25			506.47 (W) 469.46 (S)
	profit for renewables, \$			290.55			653.32			281.39 (W) 638.64 (S)

and solar are considered with CPS, MCP is 15.66 \$/MW, which is lowest among all previous considered cases. From Table 7, it can be observed that, due to the lower MCP value large number of customers gets attracted to buy more power which results in increased total power trade and finally satisfying all the purchase bids. Also, due to the integration of solar and wind power suppliers in the system the requirement of supply from CPS is highly reduced. Further, with the involvement of KDM, overestimation of uncertainty is very less as compared to the underestimation in both the solar and wind power generation. This will encourage the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive.

The efficacy of the proposed algorithm is further tested on IEEE 57-bus system. The optimal double sided strategic bidding results on IEEE 57-bus test system without inclusion of wind and solar, IEEE 57-bus test system with wind power only, IEEE 57-bus test system with solar power only and IEEE 57-bus test system with combined wind-solar power by using TGSA are given in Table 8. From Table 8, it is observed that the market is cleared at MCP value of 12.45 \$/MW, total generation of CPS is 1725.99 MW, forecasted demand and total demand of large consumers are 1437.76 and 288.23 MW respectively, total power traded is 1725.99 MW, and net profit for CPS and large consumers are \$15218.99 and \$2785.20, respectively. But if only wind power is included with CPS then MCP is reduced to 12.16 \$/MW, total generation of CPS is reduced to 1684.37 MW, total demand of large consumers and total traded power are increased to 295.45 and 1734.68 MW, respectively, and the net profit of CPS is reduced to \$14580.94 which is caused by the lower value of MCP and generation of CPS. Moreover, the net profit of large consumers is increased significantly, which is caused by the lower value of MCP and higher demand of large consumers. The wind power net profit, overestimation and underestimation cost are \$218.50, \$43.77 and \$349.50, respectively. In the second case, i.e. only solar power with CPS, the net profit value, overestimation and underestimation cost is \$478.37, \$112.08 and \$239.56, respectively. For this case, the MCP value is 11.73 \$/MW, total generation of CPS 1669.34 MW which is lower than conventional and wind due to significant power generation from the solar, total demand of large consumers

and total traded power are increased to 298.76 and 1740.1 MW, respectively. Finally, when both the wind and solar are considered with CPS, MCP is 11.25 \$/MW, which is lowest among all previous considered cases.

Results for the IEEE 30-bus and 57-bus systems show that the proposed technique in this paper is more suitable to obtain the most compromising solution for multi-objective strategic bidding problem of suppliers/large buyers and not sensitive to size of the distribution system.

7 Conclusion

This study proposes an optimal double-sided bidding strategy as a multi-objective optimisation for the profit maximisation in an emerging power market for the profit maximisation of power producers and large buyers with renewable energy sources (i.e. wind and solar energy). The formulated problem is solved by TOPSIS along with GSA, and simulation results are obtained in absence and presence of both solar and wind power. Wind speed and solar irradiation uncertainties are handled, respectively, by Weibull and beta distribution of probability, and transformed into wind and solar power. Further, KDM method is used to reduce the samples of wind and solar power. In addition, the renewable energy variability is measured by terms of overestimation and underestimation. Furthermore, the uncertainty of the behaviour of rival is minimised using the function of normal distribution of probability. It is found that from obtained results, TGSA approach is effective and promising to obtain the most compromising solution for multi-objective strategic bidding problem of suppliers/large buyers. Incorporating wind and solar power also affects the bid as it reduces the CPS generation and provides less MCP value that would deliver sufficient electricity from accepted sales bids to meet all accepted purchase bids and increase the total traded power. The obtained results clearly indicate the strength of the proposed bidding strategy in solar and wind uncertainty modelling. The use of KDM algorithm is suitable for handling solar and wind uncertainty.

Table 8 Optimal bidding result for IEEE 57-bus system and with inclusion of only wind, only with solar, and combined both wind and solar using TGSA

Suppliers	α_n	Without wind and solar			Only with wind			Only with solar			Combined both		
		β_n	P , MW	Profit, \$	β_n	P , MW	Profit, \$	β_n	P , MW	Profit, \$	β_n	P , MW	Profit, \$
1	1.7365	0.019114	560.23	5465.68	0.017579	567.75	5367.50	0.011921	576	5192.08	0.018123	531.10	4580.5
2	10	0.111432	21.93	48.82	0.097830	13.79	27.82	0.064316	43.51	56.33	0.084480	21.81	22.52
3	7.1429	0.035649	139.99	603.16	0.033105	131.75	537.19	0.082650	72.11	293.85	0.052981	84.54	296.54
4	10	0.111432	21.93	48.82	0.097830	13.79	27.82	0.064316	43.51	56.33	0.084480	21.81	22.52
5	1.81	0.017100	549.99	5304.71	0.018041	541.75	5076.48	0.020247	506.54	4562.93	0.017216	550	4648.01
6	10	0.111432	21.93	48.82	0.097830	13.79	27.82	0.064316	43.51	56.33	0.084480	21.81	22.52
7	2.439	0.022968	409.99	3698.98	0.023126	401.75	3516.31	0.025278	384.16	3214.93	0.019559	410	3209.45
total			1725.99	15218.99		1684.37	14580.94		1669.34	13432.78		1641.07	12802.06
Buyers	θ_m	π_m	D , MW	Benefit, \$	π_m	D , MW	Benefit, \$	π_m	D , MW	Benefit, \$	π_m	D , MW	Benefit, \$
1	30	0.057297	200	1910.99	0.055857	200	1968.87	0.122814	148.76	1832.73	0.110761	169.28	2027.59
2	25	0.142292	88.23	874.21	0.134565	95.45	952.68	0.042458	150	1315.54	0.089328	150	1387.36
total			288.23	2785.20		295.45	2921.55		298.76	3148.27		319.28	3414.95
	MCP, \$/MW		12.45			12.16			11.73			11.25	
	Q(MCP), MW		1437.76			1439.22			1441.35			1443.75	
	total traded power, MW		1725.99			1734.68			1740.1			1762.14	
	renewable dispatch, MW					50.31			70.76			50.31 (W)	
												70.76 (S)	
	overestimation cost for renewable, \$						43.77			112.08			40.50 (W)
													107.50 (S)
	underestimation cost for renewable, \$						349.50			239.56			323.34 (W)
												229.76 (S)	
	imbalance cost for renewable, \$						393.27			351.64			363.84 (W)
													337.26 (S)
	profit for renewable \$						218.50			478.37			202.15 (W)
													458.79 (S)

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