IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 9 December 2023, accepted 19 December 2023, date of publication 16 January 2024, date of current version 2 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3355009

RESEARCH ARTICLE

Dual-Sided Involvement of Energy Optimization and Strategic Bidding in Wind-PV System to Maximize Benefits for Customers and Power Providers

PRAMESH KUMAR[1], YOGENDRA KUMAR[1], KAUSHAL KISHOR AHIRWAR[1], ARUN KUMAR YADAV[3], (Member, IEEE), KUNDAN KUMAR[4], (Senior Member, IEEE), SANTOSH KUMAR SUMAN[5], AND TARUN SHRIVASTAVA[2]

[1]Department of Electrical Engineering, Maulana Azad National Institute of Technology Bhopal, Bhopal, Madhya Pradesh 462003, India
[2]Electrical Engineering Department, G. H. Raisoni Institute of Engineering and Technology, Nagpur, Maharashtra 440036, India
[3]Department of Electrical Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh 226201, India
[4]Department of Electrical Engineering, National Institute of Technology Manipur, Imphal, Manipur 795004, India
[5]Department of Electrical Engineering, Maharana Pratap Polytechnic, Gorakhpur, Uttar Pradesh 273015, India

Corresponding author: Kundan Kumar (kundan01012016@gmail.com)

ABSTRACT Global warming is causing industrial development to increase greenhouse gas emissions, impact power provider economies, and potentially pose a solution through renewable energy. In order to solve these issues, the research offers a dual strategic auction difficulty for renewable energy market clear prices (MCPs) to maximize supplier and buyer revenues while mitigating rival unpredictability and renewable vacillation power supply sources. The study uses scenario reduction techniques, including Beta and Weibull distribution of probability, forward-reduction technique, and underestimation and overestimation of the cost function to manage uncertainties in renewable energy. The Gravitation Search algorithm and a hybrid approach ordered weighted average distance (OWAD) combined, with Topsis operational gravitational search algorithm TOGSA (OWAD-TOGSA), are used to solve the multi-objective issue. The study evaluates the performance of IEEE standard 30-bus and 57-bus test systems and an Indian 75-bus operational system to solve a problem involving wind and sun energy in spite of its volatility. The proposed bidding approach is feasible and could increase revenue by nearly 10 %, potentially improving efficiency for electric energy-producing utilities and consumers, and its findings will be beneficial for similar research using optimization techniques.

INDEX TERMS Electricity trading, renewable energy market, dual side optimum bidding strategy, market clear prices, probability distributions, solar energy, wind energy.

I. INTRODUCTION

Global deregulation has transformed traditional power utilities into a competitive electricity market, encompassing day-ahead, real-time, and ancillary services markets. GENCOs must optimize generation capacity allocation to various markets to maximize profit in a deregulated environment, with bidding strategies being crucial for increasing profits [1], [2], [3]. Developing an optimal bidding strategy is typically based on GENCOs, technical constraints, and anticipating competitor and market behavior. The PoolCo model is a common electricity market characteristics GENCOs develop the optimum bidding strategies comprised of sets of price-making pairs. Moreover, power providers competitively traded are bid for their generation cost to affect more than the marginal price for making a profitable power generation system. When

The associate editor coordinating the review of this manuscript and approving it for publication was Ton Duc Do.

power generation systems are participating to take the more beneficial market and implementation through giving in to their individual auction saying as charges additional than the marginal prices such activities of power generation system are knowable strategic bidding systems of power generation companies [4]. GENCOs should bid above their marginal cost to maximize profit in oligopolistic electricity markets, even offering a price over their marginal revenue to maximize profits in a perfectly competitive market. Therefore, GENCOs' first priority at the present is to establish the best possible bidding strategy [5]. The restructuring led to market deregulation and changes in competitive, technological, and regulatory settings, altering the power system's primary objective, resulting in unfair strategic pricing for competitors' profit maximization [6]. Inherently introduce the bidding strategies issues for power provider utilities and researchers have done several works for the development of bidding strategies with a different timeline. The power provider organization faces a struggle due to the indeterminate embodiment of energy requests and its rival schedules [7]. Furthermore, from the standpoint of power suppliers and consumers, strategic bidder faces difficulties, this category of transformation is also rationalized by the existing condition as such an unpreventable social assistance necessity [8]. Researchers develop bidding strategies [9] for power provider organizations [10], facing challenges due to uncertain demand and rival actions, addressing various timelines [11]. In a perfect electricity market, power suppliers bid primarily on marginal cost. Strategic bids involve producing profits above and beyond marginal production costs [12]. Whenever a power supplier can successfully increase its profits through a strategic bid or any other method rather than cost reduction, it is said to have market power [13].

Thus, strategic bidding issues significantly impact the financial operations of the deregulation of grid electricity auctions. The electricity market intends to remote solar energy growth due to the assured future of solar energy. The current system is ineffective in dealing with uncertainty in renewable energy, and there is no suitable market for renewable energy bidding [9], [40]. There is limited research on solar and wind energy bidding, and more work is required for electrical utilities for profit maximization. Efficiently priced forecasting implementation is crucial for examining the impact of renewable energy on electricity prices. Integrating renewable energy sources, such as solar and wind, into electric–energy bidding is challenging due to their unpredictable nature, complex dispatching and scheduling, and underestimation and overestimation of combined generation system cost [14]. Independent service providers must develop suitable strategies for single-side bidding, considering their combined effects. India's integration of electric power plants faces competition from various distribution models, including collective wind and solar power [15], which affect the electricity market.

The literature on improving structured markets for renewable energy sources (REs) is incomplete. Optimization techniques, such as PSO (particle swarm optimization method), GA (genetic algorithm), BAI (bat-inspired algorithm), KHA (krill herd algorithm), and GSA (gravitational search algorithm), have limitations in parameter inertia, learning factors, crossover and mutation problems, poor control strategies, and exploration capability [16]. GSA, based on gravitational law and mass exchanges, offers fast, accessible global optimization solutions but reduces impulsive convergence and searchability. Opposition-based gravitational search algorithm (OGSA) techniques can overcome GSA problems by considering estimation and reverse estimation as approximation and reverse approximation. Integrating GSA with OGSA simultaneously improves optimum solution calculation [17].

The research aims to optimize benefits by combining renewable energy sources with conventional power supplies using the ordered weighted average distance (OWAD) combine with Gravitational Search Algorithm (GSA) and renewable energy as a probabilistic model to predict uncertainty and cost features.

The present research uses ordered weighted average distance (OWAD) as an optimization method for uncertain circumstances, concentrating on nearby places. The OWAD-TOGSA technique is combined with Beta and Weibull probability distribution functions to reduce uncertainty problems in electric bidding strategies. The proposed bidding model considers solar and wind power, cost functions for overestimation and underestimation, and is tested on IEEE 30 and 57 bus systems. The OWAD-TOGSA technique is applicable and suitable due to its practicality.

The arrangements for the article's content are given in the following sections. Section II contains information about the market policy. Section III presents a mathematical model for a specific market clear price (MCP), and details the proposed algorithm and the optimization framework. Section IV discusses the uncertainty surrounding solar irradiation, wind fluctuation, loads, and demand costs. Section V focuses solely on the case study in which the supplier trades power within the electricity market trading mechanism using the provided algorithms at various demand and generation times. Section, VI is given proposed algorithms that result in discussions in the competitive power market. Conferring the section VII conclusion is specified.

II. RESTRUCTURING OF THE ELECTRICITY MARKET

The restructuring phase began with the unbundling of the system, which was initially vertical integration. These eventually result in the separation of their main activities during an integrated electrical system resulting in the development of operational partitions within them. Unbundling the energy industry involves distancing transmission interactions from generation activities. Furthermore, this could differentiate distribution and transmission. Economic activities on this restructuring sector with power eventually occur also on wholesale energy markets, typically consist of even a consisting power exchange (PX) and a few trading firms. System

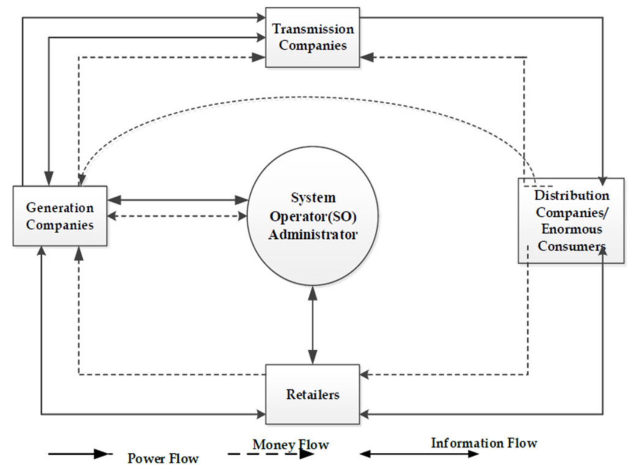

FIGURE 1. Competitive restructured electricity market.

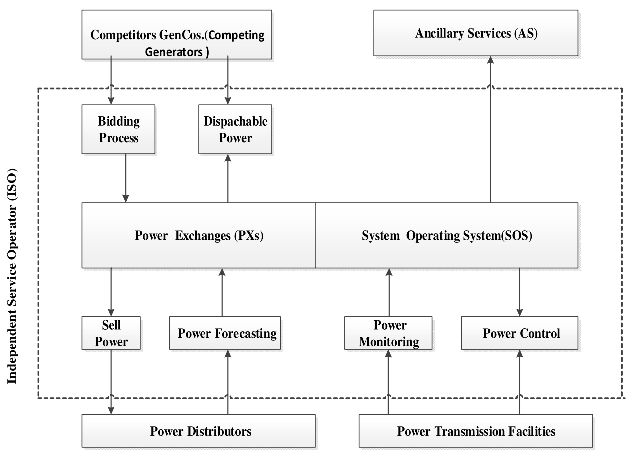

FIGURE 2. Typical independent service operator (ISO) framework.

Operator (SO) is the organization that is responsible for improving the accuracy and safety of the entire structure. It is an independent institution that is not engaged in trading in the energy market. Usually, it does not own the generation of energy, except the reserve capacity in certain situations.

The existing renewable energy auction method is unsuccessful owing to uncertainty and a lack of a sufficient market. Profit maximization requires little study about solar and wind energy bidding. Efficiently priced forecasting is critical for investigating the influence of renewable energy on power pricing. Integrating renewable energy sources into electric-energy bidding is difficult owing to its unpredictability, complicated dispatching, and underestimating of integrated generation system cost. Independent service providers must design strategies for single-sided bidding in India's electric power market, taking into account competition from diverse distribution types. Optimization approaches such as PSO, GA, BAI, KHA, and GSA provide quick global solutions, but the Typsis Opposition-based gravitational search algorithm (TOGSA) can increase optimal solution computation. To preserve system reliability and stability a range of services, like the provision of effective reserves or reactive

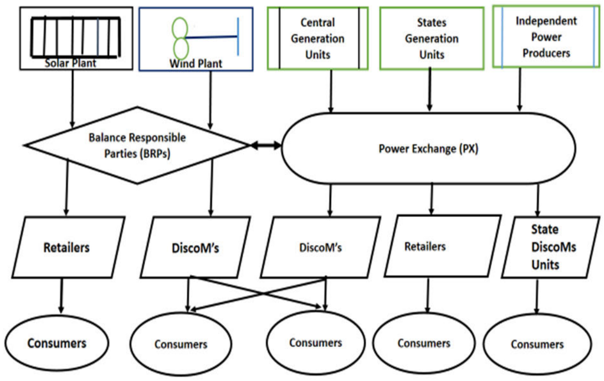

FIGURE 3. Renewable Electric Energies Market Model prices impact of PV and EV on grid stability.

power, are promoted from several other components of a system. Exchange rates and the availability of generator electricity determine the cost of DA and contingency. DAM bidding takes ten to twelve hours per day, and by seventeen hours, results have already been released with a clear volume and price [19]. Framework of the strategic restructured electrical power system shown in Figure 1.

FIGURE 1. shows the framework of the strategic level of the restructured electrical power system.

The framework of an independent service operator (ISO) throughout the event that a system operator (SO) is unbiased in every other operation as shown in Figure 2.

A. RENEWABLE ELECTRIC ENERGIES MARKET MODEL IN THE INDIAN CONTEXT

India's growing energy demand necessitates grid-interactive solar and wind energy applications. A new state-level dispatch center could offer flexible power trading for consumers and providers, matching renewable and nonrenewable energy bids. The balance responsible party (BRP) submits bids through renewable energy management centers, acquiring electricity from the Public Utility Company (PX) when production falls short of projections. The center could also bid to sell power to PX if surplus levels exist.

Solar and wind power facilities submit bids through the balance responsible party (BRP), which is financially responsible for imbalances in portfolio grid allocation points. BRP receives forecasts from renewable energy management centers (REMC) for solar and wind energy. BRP completes power generation by acquiring electricity from the Public Utility Company (PX) when production falls short of projections. BRP may also bid to sell power to PX if there is a surplus level dispatch center could offer flexible power trading for consumers and providers, matching renewable and nonrenewable energy bids. Solar and wind power facilities submit bids through the balance responsible party (BRP), which is financially responsible for imbalances in portfolio grid allocation points. BRP receives forecasts from renewable energy management centers (REMC) for solar and

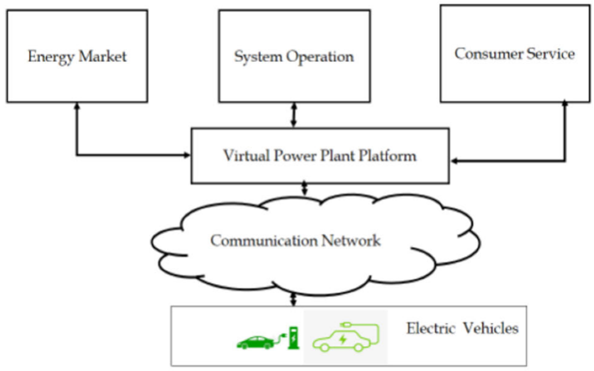

FIGURE 4. EV integration in the Indian power market.

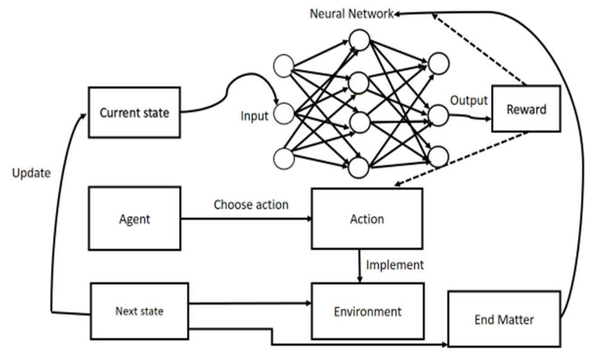

FIGURE 5. Schematic for deep reinforcement learning.

wind energy. BRP completes power generation by acquiring electricity from the Public Utility Company (PX) when production falls short of projections. This might lead to cheaper tariffs and less complicated consumer interactions [20], while distribution-level congestion might still happen. Solar energy providers are attempting to meet the demand for the upcoming day's electric auction on the electrical grid by bidding on photovoltaic energy 24 hours in advance [26]. The 15-minute power market can be used to bid on ancillary services in the solar energy grid, with the state typically managing DISCOMs under a fixed daily electricity price. Bilateral contracts offer another communication for energy trading [22].

As a consequence, the beta distribution technique is used in this research to demonstrate uncertain solar and wind generation. [22], [23]. The statistics on solar generation across time and under various circumstances. The appropriate electricity market model for renewable energy trading establishes competition among generators to provide competitive electric power features at a competitive cost to consumers, as illustrated in Figure 3.

Modern power distribution techniques like conventional energy air storage (CEAS) and solar-wind hybrid systems can develop reliable systems when solar and wind energy output is zero. However, integrating renewable energy sources into electricity profits remains a challenging task. The most important issues distressing the bidding strategies for RE_s power producers are RE_s generation, time perspective, demand, the capacity of the plant, and rival bids. The RE_s power producers have to bids optimally to increase revenue in such a scenario to avoid penalties in addition to dispatching dedicated power to the load center. Due to the enormous capability added to the production of electric energy from RE_s sources, the permeation proportion addicted to gird. The grid is the irregular situation of solar as well as wind participating in the bidding process and maximizing their individual electric energy price initiative be marginally low for precise time phases for RE_s connected grid.

B. ELECTRIC VEHICLES (EVS) IN ELECTRIC ENERGY TRADING USING RENEWABLE ENERGIES

Grid integration for electric vehicles (EVs) and solar photovoltaic (PV) systems has increased recently, essentially as a result of two objectives: reducing emissions and energy price. Numerous studies have looked into the individual effects of integrating PV and EV grids. Studies examine the effects of grid integration of PVs and electric EVs separately, and the combined in Figure 3. The unpredictable nature of renewable energies compromises security systems by reducing the supply and demand gap. According to a review of the literature, individual PV and EVs use can be harmful to the environment. Figure 4. Represents a market model for integrating micro-grids with public charging stations in Indian power market.

C. ADVANCED REINFORCEMENT LEARNING

Deep reinforcement learning can be used to build a framework for transaction regulations and policies, as well as an external environment for algorithmic strategies, similar to the electricity market [11]. The transactional actions of e-commerce sellers or customers, as well as the price of their electricity purchases, can be described as the agent's action and reward functions. A small amount of market information and actual physical states are also included in the state space.

Figure 5, Shows a schematic representation of the specific deep reinforcement training technique. Deep reinforcement learning improves Markov decision information transparency, solving computationally intensive problems by building deep neural networks, and providing insights into optimizing group behavior in power markets.

D. ADVANCED FORECASTING

Forecasting is substantial to accept for innovative estimating to change the anticipated demand to pay compensation for the uncertainty in power production generation companies from solar along with the wind. To ensure grid stability, the system designer employs a novel approach in which generation estimates are made every 5 minutes rather than every 15 minutes. Advanced machine learning techniques can be used on historical data to predict energy to match the load and demand [15].

E. BIDDING STRATEGIES FOR THE RENEWABLE ENERGY MARKET

Renewable energy production from wind and solar power is uncertain due to their large capacity. To maximize bid and participation opportunities, grid-connected renewable energy (REs) will be slightly reduced for certain time periods when favorable criteria are met. Individual modification deception in RES electricity auctions is caused by productivity inequality, leading consumers to believe in price increases. Wind-photovoltaic synchronized activity is recommended for grid reliability and cost-effectiveness, eliminating output discrepancies and economic penalties. [18]. For the hybrid REs scheme in Belgium, alliance bidding was employed to maximize return while addressing inconsistent and penalized conduct [19]. Modern power distribution techniques like conventional air storage (CEAS) and solar-wind hybrid systems can develop reliable systems when solar and wind energy output is zero. However, integrating renewable energy sources into electricity profits remains a challenging task. The most important issues distressing the bidding strategies for RE_s power producers are RE_s generation, time perspective, demand, the capacity of the plant, and rival bids. The RE_s power producers have to bids optimally to increase revenue in such a scenario to avoid penalties in addition to dispatching dedicated power to the load center. Due to the enormous capability added to the production of electric energy from RE_s sources, the permeation proportion addicted to gird. The grid is the irregular environment of solar as well as wind. Participating in the bidding process and maximizing their individual electric energy price initiative be marginally low for precise time phases for RE_s connected grid. The conception of RE_s auction is not novel for certain nations but the literature accessibility in this expanse is very fewer. Intended for mitigating the inconsistency in productivity in addition to economic penalties problems the wind-photovoltaic synchronized action is recommended for reliable and cost-effective action of the grid [18]. Towards maximizing the payoff and coping with inconsistency and penalty alliance bidding engaged on Belgium power transmission records for hybrid RE_s scheme [19]. The term of power dispatch with trodden air energy storage device, hybrid of the solar-wind organization can be beneficial to create a system reliable [20]. For a specific interval when productivity from solar and wind sources is zero at that point power from CEAS can be applied to offer correspondingly enhancing to come across the demand. The most important anxiety in penetration for RE_s into the electric profits is a challenging task. The most important issues distressing the bidding strategies for RE_s power producers are RE_s generation, time perspective, demand, the capacity of the plant, and rival bids. The RE_s power producers have to bids optimally to increase revenue in such a scenario to avoid penalties in addition to dispatching dedicated power to the load center to rid of recurrent concerns like a penalty in addition to price imbalance issues.

III. MODELLING AND BIDDING STRATEGIES ARRANGEMENT OF RENEWABLE POWER

Electrical power production and percentages of wind and solar energy plants will become more important power generators as their interconnected capabilities improve rapidly [22]. These have been considered on relatively new dimensions incorporating established wind and solar technologies and are now determining the best auction approach to electric power generation. To account for uncertainty and the accuracy of their predictions, wind, and solar energy are the pricing function's underestimation, and overestimation is recycled in a probabilistic manner. The model of solar radiation and wind speed is currently being improved. The irradiation of solar energy is represented by the Beta Probabilities Distribution Function (BPDF) and the wind velocity is to be modeled with the Weibull Probabilities Distribution Function (WPDF) [21]. Additional simulations are performed using the electric power probability distributions derived from the models.

A. MODELING ASSESSMENT OF SOLAR POWER

Strategic bidding is critical when dealing with solar electricity since it is still essential to switch the uncertainty accompanying solar irradiation [21]. Adaptation of solar irradiations is typically reliant on technical characteristics of modified solar PV modules, solar cell temperature, and solar intensity [22]. Solar irradiance and temperature, represented as [23] and [24], can be used to investigate the generation of solar electricity that may be stated as Strategic bidding is essential for solar electricity adaptation, and managing uncertainty in irradiation [25]. Adaptation depends on modified PV modules, cell temperature, and intensity [26]. Solar irradiance and temperature can be used to investigate solar electricity generation.

$$T_{Cells,t} = T_{a,} + S_{i,t}\left(\frac{T_{Not}-20}{0.8}\right) \tag{1}$$

where $T_{Cells,t}$ is cell temperature at a time intermission t in ($^{\circ}$°C, degree centigrade), $T_{a,}$ is the ambient temperature in $^{\circ}$°C

$$I_t = S_{i,t}\left[I_{Sc} + I_{tk}\left(T_{Cells,t} - 25\right)\right] \tag{2}$$

I_t is described as current at a time of intermission t

$S_{i,t}$, Solar irradiance at time interval t, T_{Cells} is nominal cell temperature in $^{\circ}$°C

I_{Sc} Short circuit current of PV cell (Amp.) and I_{tk} is current temp coefficient (mA/ $^{\circ}$°C)

$$V_{t,} = V_{Oc} - V_{tk} \times T_{Cells,t} \tag{3}$$

$V_{t,}$ is described as the voltage at time intermission t.

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

Here Fill Factor (FF) is defined as

$$FF = \frac{I_{Mpp} \times V_{Mpp}}{I_{Sc} \times V_{Oc}}$$

whereas I_{Mpp} and V_{Mpp} is the maximum obtained current and voltage, I_{Sc} and V_{Oc} are short circuit current and open circuit voltage.

B. MODELING ASSESSMENT OF WIND POWER

In order to build the best strategic bid for the development of wind generation, it is necessary to control the uncertainty related to wind speeds. A WPDF is followed by information about the wind speed at the selected location. The WPDF is given by [27].

$$W_{PDF} = \frac{k}{c}\left(\frac{v}{c}\right)^{(k-1)}\left(exp\left(-\frac{v}{c}\right)^{k}\right) \tag{5}$$

where k and c are described as shape and scale factor accordingly v, taken as wind speed in m/s.

Wind velocity parameters are influenced by topology and geography, and calculations can be performed using the objective region's rational wind velocity patterns. Weibull constraint evaluation approaches are applied in compiled works [28]. The graphical methodology for calculating k and c using the mean of historical wind (w_s) also the standard deviations (σ_{Std}) and (μ_{hws}) mean are listed below.

$$k = \left(\frac{\sigma_{Std}}{\mu_{hws}}\right)^{(-1.086)} \tag{6}$$

$$c = \left(\frac{\mu_{hws}}{\Gamma\left(1+\left(\frac{1}{k}\right)\right)}\right) \tag{7}$$

Wind velocity results are generated using historical wind speed data from anemometers placed at different turbine altitudes. WPDF generates 1000 random possibilities, which are translated into interest-driven power scenarios based on hub height. This technique is crucial due to the variability in turbine hub heights and measurements [29], and this technique is discussed as

$$v\left(h_{Est}\right) = v\left(h_{Rkh}\right)\left(\frac{h_g}{h_{kah}}\right)^{(\gamma)} \tag{8}$$

The hub transforms into a power situation by generating an electric ounce for the constrained model of wind turbine generation conditions at the appropriate height. The power estimate can be described as follows:

$$W_{(a)}(v) = \begin{cases} 0 & v \le v_{in} \\ \left(\frac{1}{2}\eta_\rho(v)\rho A_s v^{(3)}\right) & v_{in} \le v \le v_r \\ W_r & v_r \le v \le v_o \\ 0 & v_r \ge v_0 \end{cases} \tag{9}$$

Using the equation, where, $\eta_\rho(v)$), W_r and $W_{(a)}(v)$ are efficiencies, rated output power, and available power at a given wind velocity of wind producers, respectively; ρ is the air density (kg/m3);

Additionally, v_{in}, v and v_r are the cut-in, rated, and cut-out wind speed limit. A discrete and arbitrary set of wind energy-dependent variables can be generated (9). The definition of the probability of the correct part [36] in the amount of wind energy produced is

$$f_W\left(v_{in} \le v \le v_r\right) = \left(\frac{k_Z v_{in}}{CW_r}\right)\left[\frac{\left\{1+Z\left(\frac{W_a}{W_r}\right)\right\}}{C}\right]$$
$$\times\left\{-\left(\frac{\left(1+Z\left(\frac{W_a}{W_r}\right)v_{in}\right)}{C}\right)^{K}\right\} \tag{10}$$

Here Z is defined as $Z = \left(\frac{v_r - v_{in}}{v_{in}}\right)$

The probable of null wind power production [27] is characterized as

$$f_W\left[\left(v_r \le v_{in}\right) and \left(v \ge v_o\right)\right] = 1 - exp\left[-\left(\frac{v_{in}}{C}\right)^k\right] + exp\left[-\left(\frac{v_o}{C}\right)^k\right] \tag{11}$$

The probable of extreme (rated) wind power production [27] is distinct as

$$f_W\left(v_r \le v \le v_O\right) = exp\left[-\left(\frac{v_r}{C}\right)^k\right] + \exp\left[-\left(\frac{v_o}{C}\right)^k\right] \tag{12}$$

The irradiance of solar power exhibits restricted certainty because of sun positioning and constrained hours of availability. It is experimental that these records follow a BPDF which can be articulated as

$$B_{PDF}\left(S_{i,t}\right) = \left\{\begin{matrix} \frac{1}{S^{Max}_{i,}} \times \frac{\Gamma(A_t+B_t)}{\Gamma(A_t)\Gamma(B_t)}\left(\frac{(S_{i,t})}{S^{Max}_{i,t}}\right)^{(A_t-1)} \\ \left(1-\frac{(S_{,t})}{S^{Max}_{i,t}}\right)^{(B_t-1)} \end{matrix}\right\}$$
$$0 \le \frac{\left(S_{i,t}\right)}{S^{Max}_{i,t}} \le 1, A_t > 0, B_t > 0 \tag{13}$$

BPDF assemblies (A_t, B_t) are evaluated using the mean (μ_{Si}) and standard deviations (σ_{Si}) of historical solar irradiance records as tracks.

$$A_t = \mu^2_{Si}\left(\left(\frac{1-\mu_{Si}}{\sigma_{Si}}\right) - \left(\frac{1}{\mu_{Si}}\right)\right) \tag{14}$$

$$B_t = A_t\left(\frac{1}{\mu_{Si}} - 1\right) \tag{15}$$

Different BPDF fabrication methods have been developed for intermission range (0, 1), considering solar radiation nominal values and 1000 beta distributed scenarios, adjusting for PV section power scenarios [32]

$$B_{PDF}\left(S_{PV,t}\right) = \left\{\begin{matrix} \frac{(1)}{S^{Max}_{PV}} \times \frac{\Gamma(A_t+B_t)}{\Gamma(A_t)\Gamma(B_t)}\left(\frac{(S_{PV,t})}{S^{Max}_{PV,t}}\right)^{(A_t-1)} \\ \left(1-\frac{(S_{PV,t})}{S^{Max}_{PV,t}}\right)^{(B_t-1)} \end{matrix}\right\}$$
$$0 \le \frac{\left(S_{PV,t}\right)}{S^{Max}_{PV,t}} \le 1, A_t > 0, B_t > 0 \tag{16}$$

C. LIMITATION OF WIND AND SOLAR ENERGY SYSTEM

The development reduction technique uses the Kantorovich Distance Matrix (KDM) [27], The KDM procedure estimates and correlates scenarios after 1000 wind and solar energy effects, considering the probability gap between different development strategies. It creates a KDM with ideal scenarios and comparison spaces. The probability gap between any two different development strategies that result in a similar stochastic process is known as K D. In the K D procedure, the succeeding stages are used for situations in tradable. Every grouping of scenarios is given consideration by the KD [28] which creates the KDM that contains ideal scenarios and comparison spaces between them. The evaluation of the distance between two situations, v^i and v^j, is provided by

$$KD\left(v^i, v^j\right) = \left(\sum_{i=1}^{\eta l} \left(v^i - v^j\right)^2\right)^{1/2} \quad (17)$$

Discover an unlike adjoining scenario for each scenario $\boldsymbol{v^j}$ namely the scenario $\boldsymbol{v^j}, \boldsymbol{j} \neq \mathbf{1}$ of the least possible KD to asses consequence $\boldsymbol{Min\ KD}\left(\boldsymbol{v^i}, \boldsymbol{v^j}\right)$.

$$Min\left\{KD\left(v^i, v^j\right)\right\} \times P\left\{v^i\right\} \quad (18)$$

According to this tradition, the development of the disconnected entity is determined by the following conditions

- Proportional imminence to diverse scenarios too.
- Small possibility of the existence.
- Eliminate one consequence and build a new KDM. Consequently, the prospect of an unconcerned situation is additional to the possibility of the setup which is nearby it.
- Repeat previous Stages to eliminate one scenario in every single iteration until then bring to a standstill condition reached.

D. EVALUATION OF THE WIND AND SOLAR ENERGY AGGREGATE STRATEGY FOR BIDDING MODELING

The organized wind (W_{gp}) and solar (S_{gp}) power is acquired using KDM, and the corresponding probabilities are computed as follows

$$S_{gp} = \sum_{i=1}^{v_i} S_{ai} \times P_{Robi} \quad (19)$$

$$W_{gp} = \sum_{i=1}^{v_i} W_{ai} \times P_{Robi} \quad (20)$$

E. WIND AND SOLAR ELECTRIC POWER ESTIMATION

The unbalanced price tag for wind and solar energy is affected by the difference between expected and real power, which is the total amount of underestimation as well as overestimation of service charges as follows

$$IMC\left(W_{Gn}\right) = O_c\left(W_{Gn}\right) + U_c\left(W_{Gn}\right) \quad (21)$$

$$IMC\left(WS_{Gn}\right) = O_c\left(S_{Gn}\right) + U_c\left(S_{Gn}\right) \quad (22)$$

where $IMC\left(W_{Gn}\right)$ imbalance cost of wind, $IMC\left(S_{Gn}\right)$ for solar $O_c\left(W_{Gn}\right), U_c\left(W_{Gn}\right), O_c\left(S_{Gn}\right), U_c\left(S_{Gn}\right)$ are overestimation and underestimation cost are significant issues in wind power, with solar power, overestimation being more destructive than underestimation.

F. EVALUATION OF OVERESTIMATION ALONG WITH UNDERESTIMATION FOR THE AVAILABLE SOLAR AND WIND ENRGY PRODUCTION

Electric power difference significantly impacts overestimating solar and wind energy providers, as organized solar and wind energy scenario is framed as follows

$$O_c\left(S_{Gn}\right) = K_o \times \left(\int_0^{S_{Gn}} \left(S_{Gn} - S_a\right) \times f\ S_a\left(S_a\right) \times dS_a\right) \quad (23)$$

$$O_c\left(W_{Gn}\right) = K_o \times \left(\int_0^{W_{Gn}} \left(W_{Gn} - W_a\right) \times f\,SW_a\left(SW_a\right) \times dW_a\right) \quad (24)$$

The cost of underestimating solar and wind energy production will be determined by these factors. This is excessive, especially given the possibility of excess electricity. As a result, this organizes without specifying exact price tag relatively it characterizes penalty duration for the depletion of available generation resources

$$U_c\left(S_{Gn}\right) = K_u \times \left(\int_{S_{Gn}}^{S_{Max}} \left(S_a - S_{Gn}\right) \times f\ S_a\left(S_a\right) \times dS_a\right) \quad (25)$$

$$U_c\left(W_{Gn}\right) = K_u \times \left(\int_{W_{Gn}}^{W_{Max}} \left(W_a - W_{Gn}\right) \times fW_a\left(W_a\right) \times dW_a\right) \quad (26)$$

G. ELECTRICITY BIDDING ESTIMATION INCORPORATE INCLUDING RENEWABLE POWER TRADERS

Improved electric power duration and scale constraints, MCP, and objective utilities are characterized as

Electric power set of scale constraints

(a) Single Side, Generator

$$\sum_{M=1',t=1'}^{CPS,t} PG_{M,t} + \sum_{x=1',t=1'}^{RPS,t} RG_{x,t} = D\left(R_{s,t}\right) \quad (27)$$

(b) Double Side Combine Generator and Customer

$$\sum_{M=1',t=1'}^{CPS,t} PG_{M,t} + \sum_{x=1',t=1'}^{RPS,t} RG_{x,t} = D\left(R_{s,t}\right) + \sum_{n=1',t=1'}^{LB,t} CD_{n,t} \quad (28)$$

H. CALCULATION OF MARKET CP_S

Single Side, Generator

$$R_{S,t} = \left(\frac{D_{C,t} - \sum_{x=1,t=1}^{RPS,t} RG_{x,t} + \sum_{M=1,t=1}^{CPS,t} \frac{\propto_{M,t}}{\beta_{M,t}}}{K + \sum_{M=1,t=1}^{CPS,t} \frac{1}{\beta_{M,t}}}\right) \quad (29)$$

Double Side Combine Generator and Customer

I. PROBLEM ORIGINATION AS IN DUAL-SIDED POOL ELECTRIC ENERGY TRADE BY COMBINING RENEWABLE ENERGIES

According to the use of clean renewable power generation, the objective assessment of market participants' profit development on single-side electric energy markets are reforming as opportunities fade.

$$F_D\left(\propto_{M,t}\ \beta_{M,t}\right) = \left(R_{D,t} \times PG_{DM,t}\right) + \left(R_{D,t} \times RG_{x,t}\right) - PCD_{M,t}\left(PGSD_{M,t}\right) - IMC_{x,t}\left(RG_{x,t}\right) \tag{31}$$

$$F_D\left(\phi_{N,t}\varphi_{M,t}\right) = PCD_{N,t}\left(CD_{N,t}\right) - R_{D,t} \times \left(CD_{N,t}\right) \tag{32}$$

SUBJECT TO: Electric power balance constraints as in given (28) Power and demand inequality constraints and renewable power constraints as given in equations

$$PG_{Min,S,M,t} \leq PG_{S,M,t} \leq PG_{Max,S,M,t} \tag{33}$$

$$PG_{Min,D,M,t} \leq PG_{,D,M,t} \leq PG_{Max,,D,M,t} \tag{34}$$

$$CD_{Min,N,t} \leq CD_{N,t} \leq CD_{Max,N,t} \tag{35}$$

PSs attempt to predict other suppliers' bid methods and behavior, but face challenges in predicting rivals' behavior due to the interrelation of bid parameters. To solve this, they use the joint probability distribution function (pdf) in equation

This PDF can be displaying as in compact nature

$$(\pi_n, \varphi_n) \sim M \left\{ \begin{bmatrix} \mu_n^{(\pi)} \\ \mu_n^{(\varphi)} \end{bmatrix}, \begin{bmatrix} \left(\sigma_n^{(\pi)}\right)^2 & \rho_n \sigma_n^{(\pi)} \sigma_n^{(\varphi)} \\ \rho_n \sigma_n^{(\pi)} \sigma_n^{(\varphi)} & \left(\sigma_n^{(\varphi)}\right)^2 \end{bmatrix} \right\} \tag{37}$$

Here, the collective distribution considerations are $\mu_n^{(\pi)}$, $\sigma_n^{(\varphi)}$, $\sigma_n^{(\pi)}$ and $\sigma_n^{(\varphi)}$, the coefficient of correlation between π_n and φ_n is ρ_n. $\mu_n^{(\pi)}$ and $\mu_n^{(\varphi)}$ are the mean, $\sigma_n^{(\pi)}$ and $\mu_n^{(\varphi)}$ are the standard deviations of the π_n and φ_n, respectively.

IV. INTRODUCTION ALGORITHM OF OPPOSITION GRAVITATIONAL SEARCH FRAMEWORK (OGSA)

Algorithm for Searching Gravitational Sectors (GS Algorithm) usage electrical system problems and keep striving for optimum results., since this algorithm has the most flexible constraints. Its abnormally large item modifies the gravitational constant that is used to enhance the accuracy of the search. Variability is used to organize the population's initializing in the GSA approach, and planned unpredictability is utilized to ascertain the inactivity of specific parameters. Whereas if randomized estimation is close to the ideal outcome, convergence can occur quickly. Moreover, the randomly selected estimation may deviate significantly from the ideal case. In the worst-case scenario, this undesirable situation may result in an inadequate possible answer.

A. POPULATIONS INITIATION PROCESS

Consider the case in which there are N agents (aggregates) and the y^{th} agent's status is expressed as:

$$\lambda_y = \left(\lambda_{y,}^1 \ldots\ldots\ldots\ldots \lambda_{y,}^D \ldots\ldots\ldots \lambda_{y,}^M\right) \tag{38}$$

where $\lambda_{y.}^D \in \left\{\lambda_{y,}^D U_y^D\right\}$ the agent position in the dimension and M is the extent of search space and higher bounds of agents in the aspect. is indeed the position of a agents in D^{th} dimension, M is just the size of the search process, and $\lambda_{y,}^D U_y^D$ are indeed the lower and upper boundaries for the y^{th} agents in the D^{th} perspective.

B. ESTIMATE OF FITNESS AND AGENT ACCELERATION OF OPPOSITION PHENOMENON IN GSA

The most appropriate outcome of equation (31) is expected as a fitness function fit_Z in this position.

The fitness evaluation is adapted for the calculation of the weight of each agent in the GSA, the calculation of the mass as follows

$$M_y(i) = \frac{M_y(i)}{\sum_{j=1}^{N} M_j(i)} \tag{39}$$

Here, $M_y(i) = \frac{f_{ity}(i) - Worst(i)}{best(i) - Worst(i)}$ where, $M_y(i)$ is the normalization of mass of y^{th} agent at i^{th} iteration also $Worst(i)$, $best(i)$ be able to perform at both the lowest and highest fitness levels agents at i^{th} iteration.

Gravitational constant $\mathbf{G_{(i)}}$ is denoted by

$$G(i) = G \times \left(1 - \frac{iteration}{Total\ iteration}\right) \tag{40}$$

Here, $G = C_{D\in(1,2,3\ldots\ldots.M)}^{Max}\left(|\ \lambda_u^d - \lambda_l^d\ |\right)$ where c is a value for the searching interval.

The acceleration $a_i^D(i)$ interim on y^{th} agent on i^{th} iteration is estimated as follows:

$$a_y^D(i) = \sum_{\substack{j \in G_{best},\\ j \neq y}} rand_j G(i) \frac{M_y(i)}{R_{yj}(i) + E} \left\{\lambda_u^d(i) - \lambda_j^d(i)\right\} \tag{41}$$

where, the initial setting of 2% of the agents is determined G_{best} using best value of fitness and calculation for greatest mass $rand_j$ is needed the constant random variable in the Interval (0,1).

$$R_{D,t} = \left(\frac{D_{C,t} - \sum_{x=1,t=1}^{RPS,t} RG_{x,t} + \sum_{M=1,t=1}^{CPS,t} \frac{\propto_{M,t}}{\beta_{M,t}} + \sum_{N=1,t=1}^{LB,t} \frac{\emptyset_{N,t}}{\varphi_{N,t}}}{K + \sum_{M=1',t=1'}^{CPS,t} \frac{1}{\beta_{M,t}} + \sum_{N=1',t=1'}^{LB,t} \frac{1}{\varphi_{N,t}}}\right) \tag{30}$$

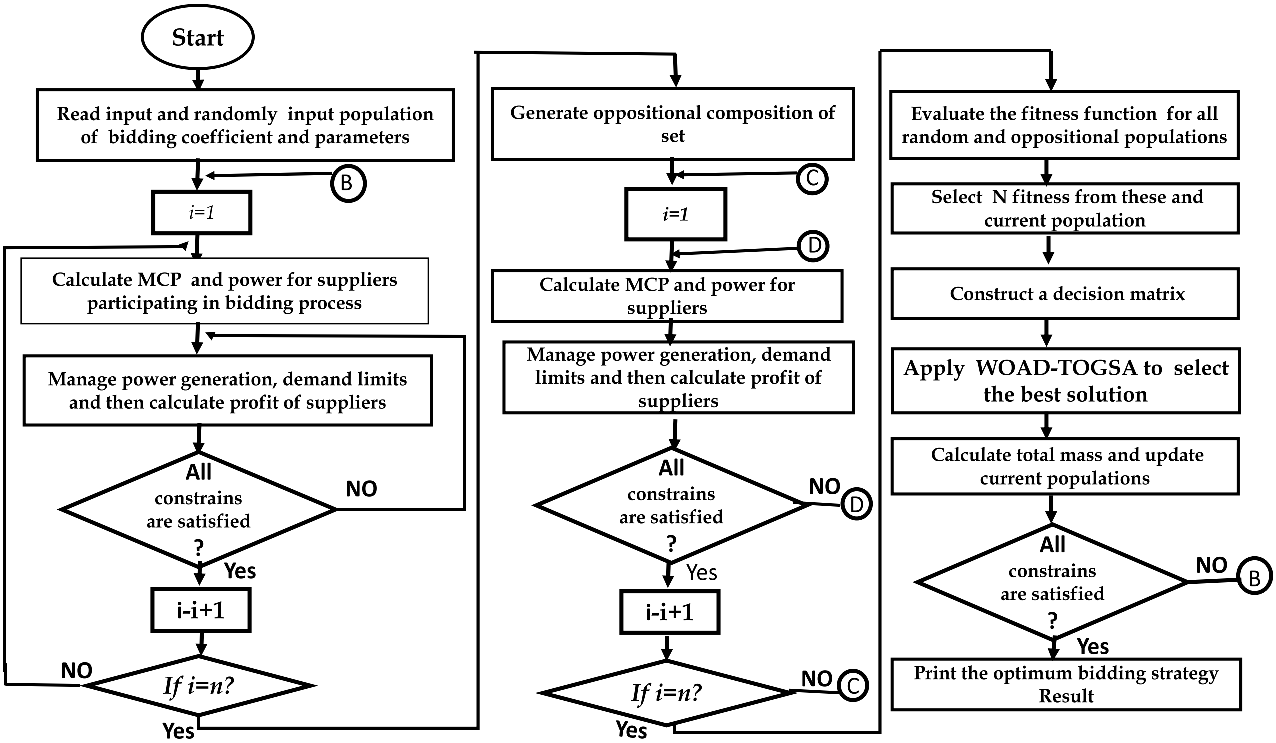

FIGURE 6. Solution techniques WOAD-TOGSA for optimal bidding.

Structure a consistent selection matrix to transmute all dimensional functions convert into non-dimensional functions. The factors of matrix might be characterized by

$$F_{ab} = \frac{O_{ab}}{\sqrt{\sum_{a=1}^{N_1} O_{ab}^2}} \forall a \epsilon N_1, \quad b \epsilon N_2 \tag{42}$$

where, N_1 remains the number of elements and Oab is the value of a^{th} element of b^{th} objective.

C. ORDER WEIGHTED AVERAGE DISTANCE TECHNIQUES (OWAD)

The term "OWAD operator" is a combination of "OWA operator" and "distance measure" to describe the decision-making attitude [30].

By combining the two different distance aggregation methodologies, the authors provide novel multiple-criteria decision-making processes. Combining the Order of Preference by Similarity (TOPSIS) method with the ordered weighted average distance (OWAD) operator to optimize solutions based on similarities to the best one. The TOPSIS technique computes the distance between alternatives to the positive ideal solution and the negative ideal solution and then chooses the best solution based on the degree of closeness. However, the decision-attitude producer's is not considered.

An OWA optimization techniques operator of dimensions n is a mapping [31] given by $\boldsymbol{OWA} : \boldsymbol{R^m} \dashrightarrow \boldsymbol{R}$ It is accompanied by a corresponding weighting vector W of size m, so $\sum_{J=1}^{m} \boldsymbol{W_J} = \mathbf{1}$ and $\boldsymbol{W_J} \in \{\mathbf{0} \mid 1\}$ then

$$OWA\left(a_1, a_2, \ldots\ldots a_m,\right) = \sum_{J=1}^{m} W_J b_J \tag{43}$$

where $\boldsymbol{b_J}$ is given as $\boldsymbol{J^{th}}$ largest $\boldsymbol{a_i}$ also R given as set of real number.

D. THE STEPS TO COMBINE THE OWAD OPERATOR WITH THE TOPSIS APPROACH

In this section, the algorithm for the proposed model is explained. Two stages of external and internal fusion schemes are presented, where external fusion scheme deals with the aggregation of majority opinion of experts and internal fusion

$$Pdf\left(\pi_n, \varphi_n\right) = \frac{1}{2\pi \sigma_n^{(\pi)} \sigma_n^{(\varphi)} \sqrt{1-\rho_n^2}} \times exp\left\{\frac{1}{2\left(1-\rho_n^2\right)} \times \left\lfloor \left(\frac{\pi_n - \mu_n^{(\pi)}}{\sigma_n^{(\pi)}}\right)^2 + \left(\frac{\varphi_n - \Psi_n^{\varphi}}{\sigma_n^{(\varphi)}}\right) \times -\frac{2\rho_n\left(\pi_n - \mu_n^{\varphi}\right)\left(\varphi_n - \mu_n^{(\varphi)}\right)}{\sigma_n^{(\pi)} \sigma_n^{(\varphi)}} \right\rfloor\right\} \tag{36}$$

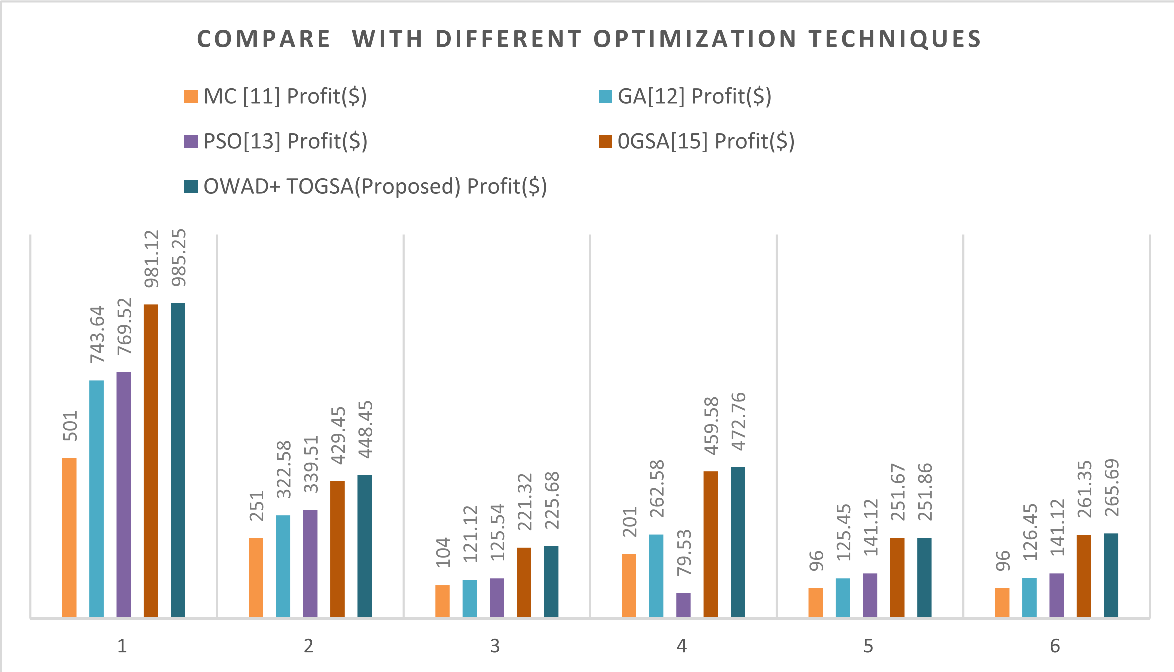

FIGURE 7. Compare of various optimization techniques and proposed technique.

scheme deals with the implementation of decision strategies, the proportion of criteria to consider.

It is necessary to compute the normalized decision-matrix. The normalized value of b_{jl}, $j = 1, 2, \ldots, m$, $l = 1, 2, \ldots, n$ is calculated as follows:

$$b_{jl} = \frac{a_{j,l}}{\sum_{l=1}^{m} a_{j,l}} \tag{44}$$

Calculate the weighted and normalized decision-matrix. The weight normalization values $C_{j,l}$ is calculated according as

$$C_{j,l} = W_j * b_{j,l}, \quad j = 1, 2, 3, \ldots m, l = 1, 2, 3 \ldots . n \tag{45}$$

where W_l is the weight of the j^{th} criterion G_j and $\sum_{j=1}^{m} W_j = 1$

Then choose the most appropriate response, both positive and negative as:

$$\begin{aligned} C^+ &= C_1^+, C_{2,}^+ C_3^+ \ldots\ldots\ldots\ldots\ldots . C_m^+ \\ &= \{(MaxC_{jl}\ (l \in I)\ (MinC_{jl}(j \in J)\} \end{aligned} \tag{46}$$

$$\begin{aligned} C^- &= C_1^-, C_{2,}^- C_3^- \ldots\ldots\ldots\ldots\ldots . C_n^- \\ &= \{(MinC_{jl}\ (l \in I)\ (MaxC_{jl}(j \in J)\} \end{aligned} \tag{47}$$

where I is associated with the cost criteria and J is associated with the benefit criteria.

E. POSITION AND VELOCITY UPDATING OF THE AGENTS

The location and velocity of the agents are determined by Equation (34) in the next $(i + 1)$ iteration.

$$\left\{ \begin{array}{l} v_k^D(i+1) = rand_k \times v_k^D(i) + a_k^D(i) \\ \lambda_k^D(i+1) = \lambda_k^D(i) + v_k^D(i+1) \end{array} \right\} \tag{48}$$

TABLE 1. Values of log probability, mean, and variances for numerous historical distributions of solar irradiance.

Distributions	Normal Fit Values	Rayleigh Fit Values	Weibull Fit Values
Log Like hood Values	-60.697	-65.7623	-60.5413
Mean Values	5.19845	4.86383	5.21237
Variance values	3.03953	6.34246	3.00065

where $rand_k$ is given as a random number concerning space [0, 1]; $v_k^D(i)$ is the velocity of k^{th} agent at D^{th} trait during the i^{th} iteration; $\lambda_k^D(i)$ is the location of k^{th} agent at the D^{th} trait during the i^{th} iteration.

V. SOLUTION POCEDURE

In the problem's specified search space, established population dimensions (N) and a randomly generated primary population develop input data for the measured test arrangement intended for the double side bidding strategy and the proposed WOAD-TOGSA regulation. Power providers' bidding coefficients are based on established population dimensions (N) and a randomly generated main population (M,t). Determined the market clearing price in accordance with (30), as shown at the bottom of page 8, the dispatch of each generator in accordance with (15), and the demand of each major client in accordance with (16). Consider the following: power generation constraints (33), demand limits (34), and arrangement load balance (35). (30) Estimate

TABLE 2. Values for various distributions' log Likelihood, mean, and variance for wind power.

Distributions	Normal Fit Values	Rayleigh Fit Values	Weibull Fit Values
Log-Like hood Values	-47.2383	-35.0039	10.1534
Mean Values	0.523167	0.52.2975	0.527209
Variance values	0.0759554	0.0739105	0.06835

TABLE 3. Complete KDM for a reduced ten-scenario set with wind energy outputs and probabilities.

Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	W_a (MW)	Probability	Min (KD)
1.	0	31.794	51.71	81.36	89.08	108.91	127.2	141.3	164.9	179.51	14.40	0.234239	27.856
2.	27.852	0	23.852	48.51	64.24	79.07	99.27	113.5	136.8	151.62	42.25	0.443627	23.851
3.	51.692	24.003	0	24.66	39.38	57.23	75.42	91.53	113.2	1319	66.10	0.17136	23.852
4.	76.349	47.95	24.66	0	15.74	31.57	49.77	64.89	90.44	103.12	89.75	0.080678	15.731
5.	92.104	64.321	40.38	15.74	0	16.86	35.05	49.16	72.73	87.41	106.51	0.025699	15.732
6.	109.11	80.862	57.22	32.56	16.85	0	18.21	32.33	55.89	70.57	123.32	0.025057	16.841
7.	127.11	98.9341	75.43	50.76	35.05	18.21	0	14.12	37.68	52.38	141.51	0.011019	14.12
8.	141.32	113.422	89.53	64.88	49.16	32.33	14.12	0	23.57	38.26	155.62	0.005095	14.13
9.	164.79	137.013	113.21	89.53	72.73	55.89	37.68	23.57	0	14.68	179.21	0.002546	14.68
10.	179.53	151.61	127.81	103.21	88.37	70.57	52.37	38.27	14.68	0	193.91	0.000853	14.68

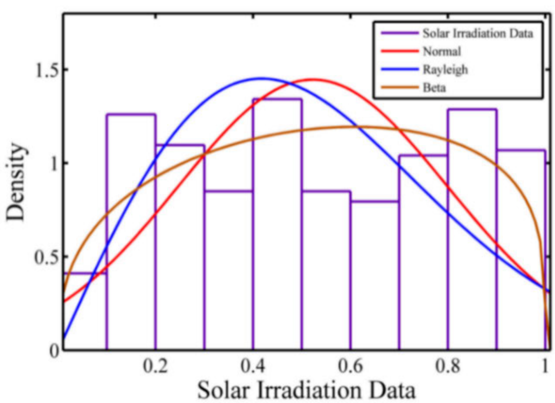

FIGURE 8. Historic solar irradiance information from Barnstable city, Massachusetts, USA, for a period of one hour (1300–1400 hrs.) Fitted with distribution.

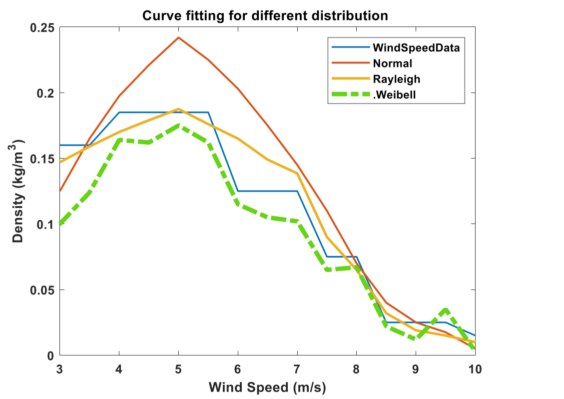

FIGURE 9. Historically, single-hour (1300-1400 hours) wind velocity data for Barnstable, Massachusetts, USA.

the profit of each electricity supplier at (31) and the profit of each consumer at (36), as shown at the bottom of page 9. Addition of the solution of (31) and (36) for entirely random (λ) in addition opposite ($O\lambda$) population respectively as 0.5 $*$ [(31) + (36)]. Estimate the solution of (31) in addition (36) for all random (λ) and opposite ($O\lambda$) population compute the answer to (31) plus (36). Calculate the optimal number of fittest agents beginning with the current population (λ) and proceeding to the opposing population ($O\lambda$) based on the current population (λ). Make a decision matrix as follows: (42) Describe the OWAD-TOPSIS strategy for selecting the best solution from (31) and (36) with the highest RCI value in accordance with (14) as the fitness function and consistent fittest agents.

A. OPTIMIZATION TECHNIQUES FLOW CHART

The flow chart which verifies the optimal solution is shown in Figure 6, and calculate the optimal solution for proposed optimization techniques through follow step by step calculation procedure.

TABLE 4. Final KDM with solar power outputs and their probabilities for reduced ten numbers of scenarios.

Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	Wa (MW)	Probability	Min (KD)
1.	0	31.794	51.71	81.36	89.08	108.91	127.2	141.3	164.9	179.51	14.40	0.234239	27.856
2.	27.852	0	23.852	48.51	64.24	79.07	99.27	113.5	136.8	151.62	42.25	0.443627	23.851
3.	51.692	24.003	0	24.66	39.38	57.23	75.42	91.53	113.2	1319	66.10	0.17136	23.852
4.	76.349	47.95	24.66	0	15.74	31.57	49.77	64.89	90.44	103.12	89.75	0.080678	15.731
5.	92.104	64.321	40.38	15.74	0	16.86	35.05	49.16	72.73	87.41	106.51	0.025699	15.732
6.	109.11	80.862	57.22	32.56	16.85	0	18.21	32.33	55.89	70.57	123.32	0.025057	16.841
7.	127.11	98.9341	75.43	50.76	35.05	18.21	0	14.12	37.68	52.38	141.51	0.011019	14.12
8.	141.32	113.422	89.53	64.88	49.16	32.33	14.12	0	23.57	38.26	155.62	0.005095	14.13
9.	164.79	137.013	113.21	89.53	72.73	55.89	37.68	23.57	0	14.68	179.21	0.002546	14.68
10.	179.53	151.61	127.81	103.21	88.37	70.57	52.37	38.27	14.68	0	193.91	0.000853	14.68

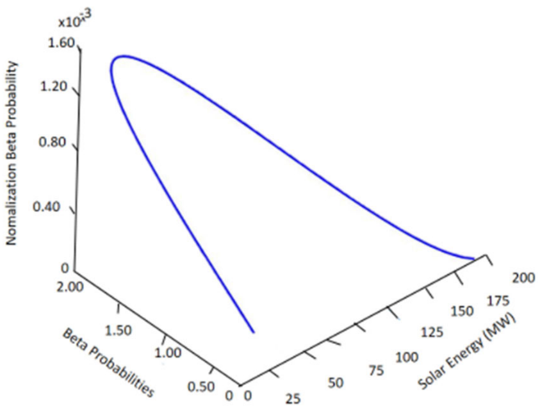

FIGURE 10. Normalize beta One-hour (1300-1400 Hr) wind velocity, as well as beta probability population density.

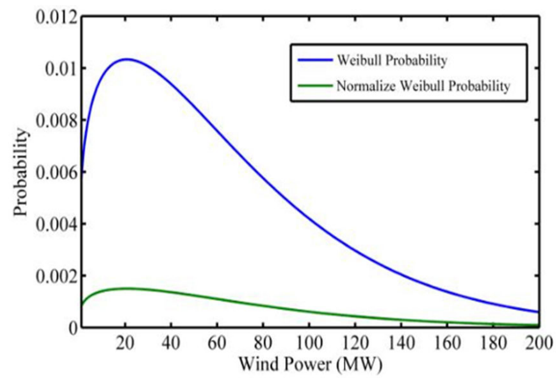

FIGURE 11. Weibull and normalized densities probability function.

B. COMPARISON OF VARIOUS OPTIMIZATION TECHNIQUES AND PROPOSED TECHNIQUE

Figure 7 shows various optimization techniques and find proposed optimization algorithm which is more appropriate in calculation of Market clear prices (MCPs) and beneficial for power providers and consumers.

VI. RESULT AND DISCUSSION PROCEDURE

This section investigates in order to maximize profit for diverse market organizations, this part looked into dual-sided bidding processes employing renewable energy sources. To solve bidding strategies, OGSA, an adapted heuristic method, and OWAD-TOPSIS, a double-sided acquisition method, are used. The study aims to increase the profit of the n^{th} PSs and consumers in the presence of renewable PSs using the IEEE 30-bus, IEEE 57 -bus and Indian -75 bus test system. The model is updated to fit single solar and single wind energy producers to the impact of renewable sources. The proposed terminology is settled by The proposed bidding model is solved by proposed OWAD –TOGSA, OGSA, GSA, PSO and GA on a 3.20 GHz, i5 processor, 4GB RAM PC, and MATLAB R2014.

CASE –I:

IEEE 30-BUS FOR COMBINING WINDS AND SOLAR ENERGY:

In this case the IEEE standard 30-bus is considered for a single solar energy data that estimates solar power [33] and solar power converted from solar irradiations taken from [36] on sun irradiation for one year data sun irradiance information from Barnstable city, Massachusetts, USA as shown in Figure 8. Table 1 shows the different

TABLE 5. Results of optimal bidding for IEEE 30-bus using a combination of wind and photovoltaic energy.

		With wind only			With solar only			With both wind and solar		
PSs	(M;t)	(M;t)	(PG) (MW)	(Profit) ($)	(M;t)	(PG) (MW)	(Profit) ($)	(M;t)	(PG) (MW)	(Profit) ($)
1.	6.01	0.075367	145.76	1261.12	0.029677	160.13	1323.59	0.024938	160.54	1278.23
2.	5.37	0.131019	92.46	572.34	0.155422	97.49	556.15	0.428103	55.64	423.81
3.	3.02	0.950465	27.64	261.96	0.52632	52.34	307.56	0.838173	45.64	297.25
4.	9.69	0.040038	120	420.97	0.203882	58.62	283.57	0.094128	89.86	338.19
5.	9.01	0.210135	42.83	175.12	0.488100	47.45	166.74	0.899021	45.64	153.62
6.	9.01	0.210097	42.83	174.49	0.488109	47.454	166.74	0.899021	45.64	153.62
Total			471.51	2863.10		463.37	2804.35		442.37	2644.68
(LBs)	(N;t)	(N;t)	(CD) (MW)	(Benefit) ($)	(N;t)	(CD) (MW)	(Benefit) ($)	(N;t)	(CD) (MW)	(Benefit) ($)
1.	30.0	0.074067	185.45	1167.52	0.082676	170.53	1211.83	0.073797	192.41	1253.54
2.	25.0	0.074032	117.87	610.21	0.062115	143.97	663.461	0.042970	150.21	706.68
Total			298.2	1768.8		321.54	1868.482		339.41	1959.31
MCP. ($/MW.)			15.59			15.48			15.11	
Q(MCP.) (MW.)			221.59			221.65			221.12	
TPT.(MW.)			498.59			543.13			563.46	
RPG. (MW.)			49.321			71.78			51.32(W), 71.77(S)	
OCRs. ($)			61.6453			149.56			57.85(W), 149.89(S)	
UCRs. ($)			471.201			331.21			463.84(W), 319.49(S)	
IMCRs. ($)			531.8434			479.76			525.68(W), 469.37(S)	
PRs. ($)			289.71			651.37			321.73(W), 639.95(S)	

probability density functions of mean and variance of solar irradiance.

Wind power is calculated using the historical single-hour (13:00-14:00) average of wind speed data collected for various distributions' log Likelihood, mean, and variance for wind power [37] as shown in Figure 9. It should be noted that the log-likelihood value of Beta distribution is better than others, indicating best fitting of the curve fitting for different distributions. fitted using curves based on various distribution Anemometer in Barnstable, Massachusetts, USA in august 2005 at a height of 39 m [38]. Table 2 shows the different probability density functions of mean and variance of wind power.

The enormous variety of scenarios predicts the uncertainty of both solar and wind energy. Despite this, only a few examples support this conclusion. The KDM framework is used to eliminate such situations and keep improving wind power modeling. TABLE 3, and TABLE 4, present 10 scenarios taken for the calculation of KDM.

Figure 10. Shows Weibull displays Beta and normalized distributions for power-produced circumstances, with Beta having higher log-likelihood values, indicating the data best fit the distribution. The probabilistic Weibull and normalized densities function is displayed in Figure 11.

TOGSA technique was found to be more effective than GSA and MC for the optimal dual-sided strategically bidding models. As a results, in this situation, the redesigned test structure is used with wind energy only, solar energy only, and wind-solar collectively, and the problem is solved using WOAD-TOGSA in the updated system, several renewable-based power sources are successively taken into account to assess their impact. System operatives are able to adjust prevailing demand, which is defined as definite demand apart from generation from wind energy for strategically wind energy bidding on the growing energy market. When the demand has changed, adjusting the bidding coefficients the new MCP is calculated Furthermore, it is assumed that the reserve coefficients and penalty coefficients

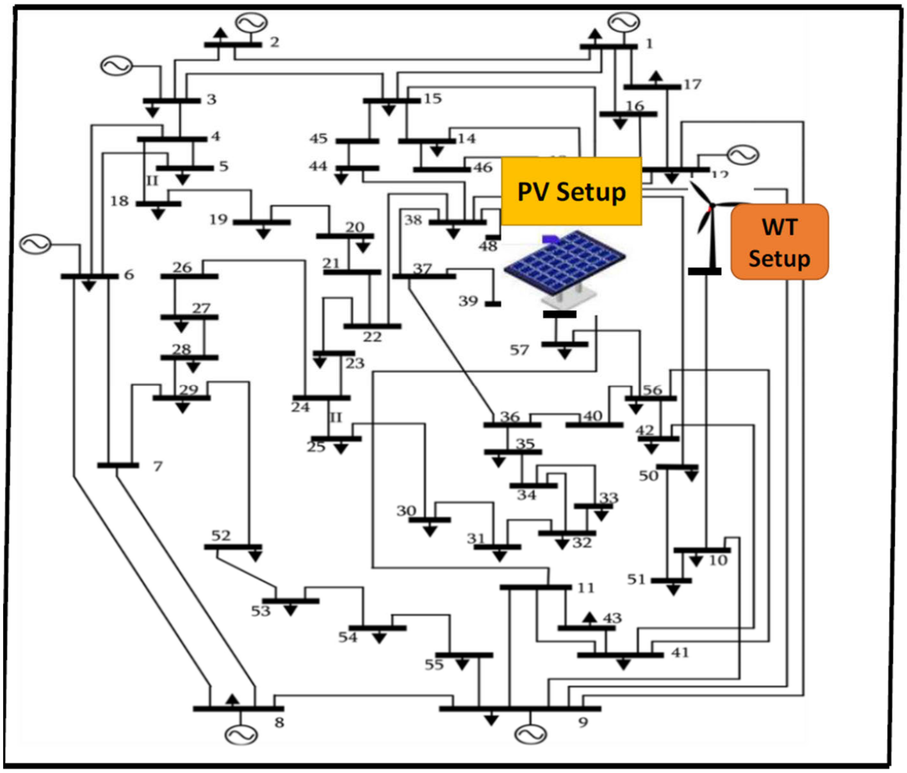

FIGURE 12. IEEE 57 -bus for combining winds and solar energy.

TABLE 6. Results of optimum bidding on the IEEE 57-bus for combining winds and solar energy.

		Consider with wind only			Consider with solar only			Consider with both wind and solar		
PSs	(αM;t)	(βM;t)	(PG) (MW)	(Profit) ($)	(βM;t)	(PG) (MW)	(Profit) ($)	(βM;t)	(PG) (MW)	(Profit) ($)
P1.	6.01	0.0069	298.59	1698.12	0.009468	298.15	1895.40	0.00932	289.36	1301.76
P2.	5.37	0.0089	109.75	899.57	0.009987	109.98	899.88	0.01124	99.78	696.05
P3.	3.02	0.0954	39..98	879.76	0.009974	121.23	999.85	0.01245	69.95	476.25
P4.	9.69	0.0087	49.708	298.47	0.125782	39.849	345..09	0.01476	39.97	291.98
P5.	9.01	0.0978	29.83	39.98	0.298500	4.945	51.27	0.01490	4.97	41.56
P6.	9.01	0.0934	13.65	241.82	0.295709	29.786	291.56	0.02491	19.85	139.75
Total			541.50	4057.72		603.94	3483.20		523.88	2947.35
(LBs)	(αN;t)	(βN;t)	(CD) (MW)	(Benefit) ($)	(βN;t)	(CD) (MW)	(Benefit) ($)	(βN;t)	(CD) (MW)	(Benefit) ($)
C1.	30.0	0.0692	89.045	1501.82	0.0798	99.52	1498.70	0.0595	121.25	1895.78
C2.	25.0	0.0621	102.502	1211.85	0.0695	110.23	1195.98	0.0382	132.74	1498..95
Total			191.547	2713.67		209.75	2694.68		253.99	3394.73
MCP. ($/MW.)			10.95			10.57			08.95	
Q(MCP.) (MW.)			221.59			221.65			221.12	
TPT.(MW.)			498.59			543.13			563.46	
RPG. (MW.)			49.321			71.78			51.32(W), 71.77(S)	
OCRs. ($)			61.6453			149.56			171.53W), 89.74(S)	
UCRs. ($)			291.543			171.21			257.29(W), 159..53(S)	
IMCRs. ($)			276.8434			231.76			212.68(W), 198.37(S)	
PRs. ($)			289.71			651.37			139.50(W), 381.32(S)	

associated with underestimations and overestimations, respectively, are each one 50% of MCP also equal to MCP. Table 5. Shows the results of the best double-sided strategic bidding using OWAD-TOGSA for the redesigned test system's wind-only, solar-only, and combination wind-solar energy.

TABLE 7. Results of optimal bidding for the Indian 75-bus operational system using a combination of wind and photovoltaic energy.

PSs	(αM;t)	Consider with wind only (βM;t)	(PG) (MW)	(Profit) ($)	Consider with solar only (βM;t)	(PG) (MW)	(Profit) ($)	Consider with both wind and solar (βM;t)	(PG) (MW)	(Profit) ($)
P1.	6.01	0.0069	298.59	1698.12	0.009468	298.15	1895.40	0.00932	289.36	1301.76
P2.	5.37	0.0089	109.75	899.57	0.009987	109.98	899.88	0.01124	99.78	696.05
P3.	3.02	0.0954	39..98	879.76	0.009974	121.23	999.85	0.01245	69.95	476.25
P4.	9.69	0.0087	49.708	298.47	0.125782	39.849	345..09	0.01476	39.97	291.98
P5.	9.01	0.0978	29.83	39.98	0.298500	4.945	51.27	0.01490	4.97	41.56
P6.	9.01	0.0934	13.65	241.82	0.295709	29.786	291.56	0.02491	19.85	139.75
Total			541.50	4057.72		603.94	3483.20		523.88	2947.35
(LBs)	$(\alpha_{N;t})$	$(\beta_{N;t})$	(CD) (MW)	(Benefit) ($)	$(\beta_{N;t})$	(CD) (MW)	(Benefit) ($)	$(\beta_{N;t})$	(CD) (MW)	(Benefit) ($)
C1.	30.0	0.0692	89.045	1501.82	0.0798	99.52	1498.70	0.0595	121.25	1895.78
C2.	25.0	0.0621	102.502	1211.85	0.0695	110.23	1195.98	0.0382	132.74	1498..95
Total			191.547	2713.67		209.75	2694.68		253.99	3394.73
MCP. ($/MW.)			10.95			10.57			08.95	
Q(MCP.) (MW.)			221.59			221.65			221.12	
TPT.(MW.)			498.59			543.13			563.46	
RPG. (MW.)			49.321			71.78			51.32(W), 71.77(S)	
OCRs. ($)			61.6453			149.56			171.53W), 89.74(S)	
UCRs. ($)			291.543			171.21			257.29(W), 159..53(S)	
IMCRs. ($)			276.8434			231.76			212.68(W), 198.37(S)	
PRs. ($)			289.71			651.37			139.50(W), 381.32(S)	

TABLE 5 shows the incorporating wind power into CPS reduces MCP to 15.59 $/MW, decreases total generation to 471.51 MW, increases demand of large consumers and total traded power to 298.2 MW and 498.59 MW, and reduces CPS net profit to $2863.10. However large consumers' net profit increases significantly due to lower MCP value and higher demand. Wind power net profit, overestimation, and underestimation costs are $289.71, $61.64, and $471.20, respectively. The second case focuses on solar power with CPS, with net profit value, overestimation, and underestimation costs at $651.37, $149.56, and $331.21, respectively. Solar power output is significant, resulting in a MCP value of 15.48 $/MW. CPS generation is 463.37 MW, lower than conventional and wind power, with increased demand and traded power. The study show that when considering combine wind and solar power with CPS, the MCP 15.11 $/MW is the lowest among all previous cases. This lower MCP value attracts more customers, increasing total power trade and satisfying purchase bids. The integration of solar and wind power suppliers reduces the need for CPS supply. Additionally, the involvement of KDM reduces overestimation of uncertainty in both generation, encouraging suppliers to bid more in real-time markets if underestimation is positive.

CASE –II:

IEEE 57-BUS FOR COMBINING WINDS AND SOLAR ENERGY:

Figure 12. Shows the IEEE 57-bus system including one solar and one wind power generation system.

In TABLE 6, Shows the results of optimum bidding on the IEEE 57-bus on consider with wind solar and combine both according to the analysis, adding wind power into CPS lowers MCP to $10.95/MW, decreases total generation to 541.50 MW, increases demand for large consumers and total traded power to 191.54 MW and 498.59 MW, and reduces CPS net profit to $2713..67. However, large consumers' net profit increases due to lower MCP value and higher demand s. ‘‘Overestimation, underestimation, and wind power net profit in the second scenario,$61.6453, $291.543 and $541.50, respectively. Solar power output with CPS is significant, resulting in a MCP value of 10.57 $/MW, net profit overestimation and underestimation are $651.37, $149.56 and $171.21 respectively. CPS generation is 463.37 MW, lower than conventional and wind power, with increased demand and traded power. The results show that when considering combine wind and solar power with CPS, the MCP 08.95 $/MW is the lowest among all previous cases. It does, however, increase the profits of large buyers to $ 3394.73. Due to the fact that lower MCP will satisfy all purchase offers, the impact of renewable sources on MCP and overall generating dispatch is significant, increasing total bidding power.

CASE-III:

INDIAN 75-BUS OPERATIONAL SYSTEM:

A practical 75-bus system in India is made up of utilities. The input data for this useful system is derived from ref. [40]. A practical 75-bus system in India is made up of utilities. The bidding strategy is designed for this instance using double-sided bidding, where large purchasers and generating utilities participate in the energy market for bidding purposes. First, the bidding model is solved using OWAD-TOPSIS and compared with without combining wind and solar energy. In this scenario, OWAD-TOGSA is then used to analyze the impact of combined wind-solar energy.

In according to TABLE 7 shows the results of optimum bidding on the Indian 75-bus on consider with wind solar and combine both according to the analysis, adding wind power into CPS lowers MCP to 10.95 $/MW, decreases total generation to 191.547 MW, increases demand for large consumers and total traded power to 191.547 MW and 498.59 MW, and reduces CPS net profit to $2713..67. However, large consumers' net profit increases due to lower MCP value and higher demand s. Overestimation, underestimation, and wind power net profit in scenario, $61.6453, $291.543 and $541.50, respectively. Solar power output with CPS is significant, resulting in a MCP value of 10.57 $/MW, net profit overestimation and underestimation are $651.37, $149.56 and $171.21 respectively. CPS generation is 463.37 MW, lower than conventional and wind power, with increased demand and traded power. The results show that when considering combine wind and solar power with CPS, the MCP 08.95 $/MW is the lowest among all previous cases. It does, however, increase the profits of large buyers to $ 3394.73. Due to the fact that lower MCP will satisfy all purchase offers, the impact of renewable sources on MCP and overall generating dispatch is significant, increasing total bidding power.

VII. CONCLUSION

This research analyzes double-sided auction processes for improving profit in solar and wind electric energy resources. The OWAD-TOGSA heuristic procedure is used to solve the double-sided bidding strategy, while Weibull and Beta probability distributions are used to organize and distort uncertainty. The KDM method is also used to control solar and wind energy models. Both overestimation and underestimation stages impact the unpredictability of intermittent electric generation. The OGSA and OWAD-TOPSIS techniques are functional and capable of identifying and solving most problems. A wind and solar power combination inhibits bidding, restricting CPS generation power and offering a lower MCP valuation. Underestimating the combined trade of solar and wind energy is more common than overestimating in action due to the importance of KDM. Solar and wind energy production companies are more willing to offer additional power bids due to ongoing economic uncertainty. Results for the IEEE standard 30-bus, IEEE standard 57-bus, and Indian 75-bus operational augmented six vendors with two stakeholders strategic bidding issues. The proposed approach measures rival behavior using the normal PDF to mitigate power market dynamics. Results show that renewable source deployment impacts the offer by decreasing CPS output and providing lowered MCP, attracting consumers and encouraging producers to reduce carbon emissions. Handling uncertainty helps RESs decide their output for bidding and saves penalties, resulting in acceptable outcomes for the uncertainty model of renewable sources.

REFERENCES

[1] Y. Wang, Y. Zheng, and Q. Yang, "Day-ahead bidding strategy of regional integrated energy systems considering multiple uncertainties in electricity markets," *Appl. Energy*, vol. 348, Oct. 2023, Art. no. 121511.

[2] E. Ni, P. B. Luh, and S. Rourke, "Optimal integrated generation bidding and scheduling with risk management under a deregulated power market," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 600–609, Feb. 2004, doi: 10.1109/TPWRS.2003.818695.

[3] A. Banshwar, N. K. Sharma, Y. R. Sood, and R. Shrivastava, "Market based procurement of energy and ancillary services from renewable energy sources in deregulated environment," *Renew. Energy*, vol. 101, pp. 1390–1400, Feb. 2017, doi: 10.1016/j.renene.2016.10.017.

[4] T. Kempitiya, S. Sierla, D. De Silva, M. Yli-Ojanpera, D. Alahakoon, and V. Vyatkin, "An artificial intelligence framework for bidding optimization with uncertainty in multiple frequency reserve markets," *Appl. Energy*, vol. 280, no. 2020, Art. no. 115918.

[5] D. E. Aliabadi, M. Kaya, and G. Şahin, "An agent-based simulation of power generation company behavior in electricity markets under different market-clearing mechanisms," *Energy Policy*, vol. 100, pp. 191–205, Jan. 2017.

[6] J. Nicolaisen, V. Petrov, and L. Tesfatsion, "Market power and efficiency in a computational electricity market with discriminatory double-auction pricing," *IEEE Trans. Evol. Comput.*, vol. 5, no. 5, pp. 504–523, 2001.

[7] U. Amin, M. J. Hossain, W. Tushar, and K. Mahmud, "Energy trading in local electricity market with renewables—A contract theoretic approach," *IEEE Trans. Ind. Informat.*, vol. 17, no. 6, pp. 3717–3730, Jun. 2021.

[8] N. Amjady and M. Hemmati, "Energy price forecasting-problems and proposals for such predictions," *IEEE Power Energy Mag.*, vol. 4, no. 2, pp. 20–29, Mar./Apr. 2006.

[9] Y. Jiang, J. Hou, Z. Lin, F. Wen, J. Li, C. He, C. Ji, Z. Lin, Y. Ding, and L. Yang, "Optimal bidding strategy for a power producer under monthly pre-listing balancing mechanism in actual sequential energy dual-market in China," *IEEE Access*, vol. 7, pp. 70986–70998, 2019, doi: 10.1109/ACCESS.2019.2919347.

[10] D. Liu, Y. Gao, W. Wang, and Z. Dong, "Research on bidding strategy of thermal power companies in electricity market based on multi-agent deep deterministic policy gradient," *IEEE Access*, vol. 9, pp. 81750–81764, 2021, doi: 10.1109/ACCESS.2021.3086002.

[11] N. Harder, A. Weidlich, and P. Staudt, "Finding individual strategies for storage units in electricity market models using deep reinforcement learning," *Energy Inform.*, vol. 6, p. 41, Oct. 2023, doi: 10.1186/s42162-023-00293-0.

[12] A. Azadeh, S. F. Ghaderi, B. P. Nokhandan, and M. Sheikhalishahi, "A new genetic algorithm approach for optimizing bidding strategy viewpoint of profit maximization of a generation company," *Exp. Syst. Appl.*, vol. 39, no. 1, pp. 1565–1574, 2012.

[13] P. Bajpai and S. N. Singh, "Fuzzy adaptive particle swarm optimization for bidding strategy in uniform price spot market," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2152–2160, Nov. 2007.

[14] R. Weron, "Electricity price forecasting: A review of the state-of-the-art with a look into the future," *Int. J. Forecasting*, vol. 30, no. 4, pp. 1030–1081, Oct. 2014, doi: 10.1016/j.ijforecast.2014.08.008.

[15] S. D. Ahmed, F. S. M. Al-Ismail, M. Shafiullah, F. A. Al-Sulaiman, and I. M. El-Amin, "Grid integration challenges of wind energy: A review," *IEEE Access*, vol. 8, pp. 10857–10878, 2020.

[16] R. Wang, F. Su, T. Hao, and J. Li, "RGSA: A new improved gravitational search algorithm," in *Proc. Int. Conf. Model., Simul. Appl. Mathematics*, Shanghai, China, vol. 160, Jul. 2018, pp. 202–207.

[17] R. K. Khadanga and J. K. Satapathy, "Time delay approach for PSS and SSSC based coordinated controller design using hybrid PSO-GSA algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 71, pp. 262–273, Oct. 2015.

[18] U. Helman, "Market power monitoring and mitigation in the US wholesale power markets," *Energy*, vol. 31, nos. 6–7, pp. 877–904, May 2006.

[19] M. A. Khan, A. M. Saleh, M. Waseem, and I. A. Sajjad, "Artificial intelligence enabled demand response: Prospects and challenges in smart grid environment," *IEEE Access*, vol. 11, pp. 1477–1505, 2023.

[20] Z. Dobrotkova, K. Surana, and P. Audinet, "The price of solar energy: Comparing competitive auctions for utility-scale solar PV in developing countries," *Energy Policy*, vol. 118, pp. 133–148, Jul. 2018.

[21] E. Ibanez, G. Brinkman, M. Hummon, and D. Lew, "A solar reserve methodology for renewable energy integration studies based on sub-hourly variability analysis," in *Proc. 2nd Int. Workshop Integr. Sol. Power Power Syst.*, Lisbon, Portugal, Nov. 2012, pp. 1–6.

[22] M. K. Behera, I. Majumder, and N. Nayak, "Solar photovoltaic power forecasting using optimized modified extreme learning machine technique," *Eng. Sci. Technol., Int. J.*, vol. 21, no. 3, pp. 428–438, Jun. 2018.

[23] E. Akarslan and F. O. Hocaoglu, "A novel adaptive approach for hourly solar radiation forecasting," *Renew. Energy*, vol. 87, pp. 628–633, Mar. 2016.

[24] A. Serban, L. S. Paraschiv, and S. Paraschiv, "Assessment of wind energy potential based on Weibull and Rayleigh distribution models," *Energy Rep.*, vol. 6, pp. 250–267, Nov. 2020.

[25] K. S. Reddy, L. Panwar, B. K. Panigrahi, and R. Kumar, "Modelling and analysis of resource scheduling in restructured power systems considering wind energy uncertainty," *Int. J. Sustain. Energy*, vol. 37, no. 8, pp. 736–760, Sep. 2018.

[26] H. Rezk, M. Aly, M. Al-Dhaifallah, and M. Shoyama, "Design and hardware implementation of new adaptive fuzzy logic-based MPPT control method for photovoltaic applications," *IEEE Access*, vol. 7, pp. 106427–106438, 2019.

[27] S. Singh and M. Fozdar, "Optimal bidding strategy with the inclusion of wind power supplier in an emerging power market," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 10, pp. 1914–1922, May 2019.

[28] S. Singh, M. Fozdar, H. Malik, I. A. Khan, S. Al Otaibi, and F. R. Albogamy, "Impacts of renewable sources of energy on bid modeling strategy in an emerging electricity market using oppositional gravitational search algorithm," *Energies*, vol. 14, no. 18, p. 5726, Sep. 2021.

[29] G. Gualtieri and S. Secci, "Methods to extrapolate wind resource to the turbine hub height based on power law: A 1-H wind speed vs. Weibull distribution extrapolation comparison," *Renew. Energy*, vol. 43, pp. 183–200, Jul. 2012.

[30] X. Liu and L. Wang, "An extension approach of TOPSIS method with OWAD operator for multiple criteria decision-making," *Granular Comput.*, vol. 5, no. 1, pp. 135–148, Jan. 2020.

[31] J. M. Merigó, D. Palacios-Marqués, and P. Soto-Acosta, "Distance measures, weighted averages, OWA operators and Bonferroni means," *Appl. Soft Comput.*, vol. 50, pp. 356–366, Jan. 2017.

[32] K. C. Sharma, P. Jain, and R. Bhakar, "Wind power scenario generation and reduction in stochastic programming framework," *Electric Power Compon. Syst.*, vol. 41, no. 3, pp. 271–285, Feb. 2013.

[33] K. Hamedani, L. Liu, R. Atat, J. Wu, and Y. Yi, "Reservoir computing meets smart grids: Attack detection using delayed feedback networks," *IEEE Trans. Ind. Informat.*, vol. 14, no. 2, pp. 734–743, Feb. 2018.

[34] H. Manoharan, Y. Teekaraman, R. Kuppusamy, and A. Radhakrishnan, "Application of solar cells and wireless system for detecting faults in phasor measurement units using non-linear optimization," *Energy Explor. Exploitation*, vol. 41, no. 1, pp. 210–223, Jan. 2023.

[35] S. Singh, M. Fozdar, H. Malik, M. D. V. F. Moreno, and F. P. G. Márquez, "Influence of wind power on modeling of bidding strategy in a promising power market with a modified gravitational search algorithm," *Appl. Sci.*, vol. 11, no. 10, p. 4438, May 2021.

[36] E. Cuevas, P. Díaz, O. Avalos, D. Zaldívar, and M. Pérez-Cisneros, "Nonlinear system identification based on ANFIS-hammerstein model using gravitational search algorithm," *Int. J. Speech Technol.*, vol. 48, no. 1, pp. 182–203, Jan. 2018.

[37] A. Adhikari, F. Jurado, S. Naetiladdanon, A. Sangswang, S. Kamel, and M. Ebeed, "Stochastic optimal power flow analysis of power system with renewable energy sources using adaptive lightning attachment procedure optimizer," *Int. J. Electr. Power Energy Syst.*, vol. 153, Nov. 2023, Art. no. 109314.

[38] S. S. Reddy and S. A. Wajid, "Swarm intelligent-based congestion management using optimal rescheduling of generators," *Int. J. Bio-Inspired Comput.*, vol. 13, no. 3, pp. 159–168, 2019.

[39] M. Singh and S. Chauhan, "Tree-based ensemble machine learning techniques for power system static security assessment," *Electric Power Compon. Syst.*, vol. 50, nos. 6–7, pp. 359–373, Apr. 2022.

[40] P. Kumar and S. K. Bharadwaj, "Optimal bidding strategies and profit maximization for micro grid combinations in electric energy market in Indian restructured environment," *Int. J. Adv. Res. Eng. Technol.*, vol. 11, no. 6, pp. 931–951, 2020.

PRAMESH KUMAR received the B.Tech. degree in electrical engineering from the Government Engineering College, IET, M. J. P. Rohilkhand University, Bareilly, India, in 2008, the master's degree from the Maulana Azad National Institute of Technology (MANIT), Bhopal, Madhya Pradesh, India, in 2010. He is a Ph.D. research scholar in electrical engineering department at the Maulana Azad National Institute of Technology (MANIT) Bhopal, Bhopal, MP, India. He works as a Faculty in various engineering colleges. His research interests include power systems, power system economics, the electricity market, renewable energy modeling, multi-agent systems, and nature-inspired algorithms.

YOGENDRA KUMAR received the B.Sc.Engg. degree from Jamia Millia Islamia, New Delhi, India, in 1991, the M.Tech. degree from MANIT, Bhopal, Madhya Pradesh, in 1998, and the Ph.D. degree from IIT Roorkee, in 2006. He is currently a Professor with the Electrical Engineering Department, MANIT. He also worked as the HOD and the Dean (S&W). He has published many research papers in reputed journals, such as IEEE TRANSACTION, international journals, and national and international conferences. His research interests include smart grids, electrical distribution systems, neural networks, and fuzzy logic. He is a Life Member of the Indian Society for Technical Society and the International Association of Computer Science and Information Technology.

KAUSHAL KISHOR AHIRWAR received the B.E. degree in electrical and electronics engineering from UIT RGPV, Bhopal, Madhya Pradesh, in 2017, and the M.Tech. degree in green technology from MANIT, Bhopal, in 2020, where he is currently pursuing the Ph.D. degree in power systems. His current research interests include power systems, optimization techniques, renewable energy, power electronics, and smart grids.

ARUN KUMAR YADAV (Member, IEEE) received the B.Tech. degree from PIT, Jaunpur, in 2007, the M.Tech. degree from NIT Patna, Bihar, in 2010, and the Ph.D. degree from Shri Venkateswara University, Gajraula, Uttar Pradesh, India, in 2019. He is currently an Associate Professor with the Department of Electrical Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh, India. His research interests include power systems, power system economics, the electricity market, renewable energy modeling, multi-agent systems, and nature-inspired algorithms.

KUNDAN KUMAR (Senior Member, IEEE) received the M.Tech. degree in electrical engineering from NIT Jamshedpur, Jamshedpur, India, in 2010, and the Ph.D. degree in electrical engineering from the University of Padova, Padua, Italy, in 2016. He is currently an Assistant Professor with the Department of Electrical Engineering, NIT Manipur. He has published more than 45 research papers in international journals and conference proceedings and five book chapters. His research interests include electric vehicles and their charging infrastructures, propulsion drive systems for EVs, application of wide bandgap semiconductor devices (such as, GaN and SiC), wireless power transfer systems, dynamic wireless charging systems, high-efficiency power converters, soft switching, multi-port converters, single-active bridge (SAB), and dual active bridge (DAB) converters. He is an Associate Member of the Institution of Engineers (IE), India. He is the Reviewer of IEEE Transactions/journals, such as IEEE Transactions on Industrial Electronics, IEEE Transactions on Power Electronics, IEEE Journal of Emerging and Selected Topics in Power Electronics, and various reputed conferences, such as IECON, PEDES, INDICON, and PEMC.

SANTOSH KUMAR SUMAN received the B.Tech. degree in electrical engineering from the AZAD Institute of Engineering and Technology, Lucknow, Uttar Pradesh, India, in 2013, the M.Tech. degree from the MMM University of Technology, Gorakhpur, Uttar Pradesh, in 2016, and the Ph.D. degree from the Electrical Engineering Department, MMM University of Technology, in 2021. He works as a faculty member of various engineering colleges. He is currently with the Department of Electrical Engineering, Maharana Pratap Polytechnic, Gorakhpur. His research interests include control system power system economics, the electricity market, renewable energy modeling, multi-agent systems, and nature-inspired algorithms.

TARUN SHRIVASTAVA received the B.E. degree in electrical engineering from MITS Gwalior, in 2008, and the M.Tech. and Ph.D. degrees in power systems from MANIT, Bhopal, Madhya Pradesh, in 2010 and 2021, respectively. He is currently an Assistant Professor with GHRIET, Nagpur. He has nine years of teaching experience. He has published two patents and two copy rights. More than ten research papers published in various Scopus, IEEE, and national/international conferences and journals. His current research interests include power systems, fuzzy logic, optimization techniques, renewable energy, power electronics, and smart grids.