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Fractional PSOGSA Algorithm Approach to Solve Optimal Reactive Power Dispatch Problems with Uncertainty of Renewable Energy Resources

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ABSTRACT The optimal reactive power dispatch (ORPD) is a major tool, and it plays a vital role for enhancement of the power system performance. ORPD is one multimodal, non-convex, and non-linear problem. Many elegant benefits can be obtained by using the renewable energy resources (RERs), but many technical issues related to the RERs including the stochastic characteristics of these resources due to continuous variations of solar irradiance and the wind speed lead to increasing the uncertainties of system. Thus, solving the ORPD problem with RERs is a crucial task. The contribution of the paper includes application a modified hybrid algorithm for solving the ORPD considering the uncertainties of the RERs and the load demand. The proposed algorithm is based on Fractional Calculus with Particle Swarm Optimization Gravitational Search Algorithm (FPSOGSA) which aims to enhance the searching capabilities of the conventional PSOGSA algorithm and overcome its tendency to stagnation. The proposed algorithm is tested on IEEE 30-bus system for reducing power losses and voltage deviation as well as enhancing voltage stability. The scenario-based method is employed to produce a set of scenarios from the uncertainties of load, wind speed and solar irradiance. The simulation results verify the effectiveness of the proposed algorithm for solving the ORPD problem with and without considering the uncertainties in the system. Furthermore, the proposed algorithm is superior compared with the state-of-the-art techniques in terms of the reduction of power losses and voltage deviations as well as the stability enhancement.

INDEX TERMS Optimal Reactive Power Dispatch, Renewable Energy Resources, Optimization, Fractional Calculus, Particle Swarm Optimization, Gravitational Search Algorithm, Uncertainty

I. INTRODUCTION

In this section, the different techniques related to the optimal reactive power dispatch (ORPD) discussed with and without integration of renewable energy resources (RERs) as well as research gap and paper contribution are given in detail.

ORPD is taking as an important consideration in the secure operation of electric systems that aims to get the best profile of the voltage and reduction of power losses by adjusting a set of control variable values including the voltages of generator, shunt VAR reactive compensators and the tap changing of the transformers. Meanwhile, optimization constraints generator reactive power capabilities, voltages of load bus, power balance and line capacities must be satisfied. Therefore, the reactive power flow is taken as the important consideration in the electrical network and cannot be avoided. Most of the loads in the electrical systems are inductive, such as transmission lines and transformers but it should be sufficient to supply VAR consumers within the limits. Otherwise, it will cuase unwanted voltage and heat loss. An objective will be set to minimize the power losses, voltage deviation and voltage stability index while the desired objective can be achieved by settings of the control variables. Nowadays, the contribution of RERs in electric power system is intensively considered [1-8].

In the past few decades, numerous optimization techniques have been studied to use conventional thermal unit for solving ORPD. These optimization techniques include gradient-based approach, linear programing, interior point, quadratic programming and non-linear programming [9-13].

However, they have some of difficulties to solve the intricated problem of ORPD such as trapping into the local minima, premature convergence and the algorithmic complexity. To resolve these problems, the development of the new meta-heuristic optimization techniques like differential evolution technique, whale optimization algorithm, sine cosine algorithm, moth-flame optimization, ant lion optimizer algorithm, cuckoo search algorithm, plant propagation algorithm, grey wolf algorithm and particle swarm optimization [14-21] are developed to overcomes these issues.

The new hybrid techniques are used for the conventional thermal units to solve ORPD. Singh and Srivastava [22] used the newly Hybrid Multi-Swarm Particle Swarm Optimization (HMPSO) algorithm to minimize the real power loss and improving the voltage stability. In this technique, a swarm is split into the sub-swarms then the sub-swarm is applied as search engine. Jirwadee et al [23] proposed an improved pseudo-gradient search PSO (IPG-PSO) using a linearly decrease chaotic weight factor led by pseudo gradient search technique. A novel hybrid population based on PSOGSA algorithm was proposed by Lenin et al [24] to minimize real power loss and voltage deviations using IEEE30 standard. Khan et al. [25] proposed the fractional PSOGSA algorithm to alleviate power losses and voltage deviations. The fractional approach was incorporated into the PSOGSA algorithm for enhancing the convergence properties of the algorithm.

However, the new developments and the generations are introduced to the electric power system due to increasing demand of electric power supply to the grid. These generations are the renewable energy resources (RERs) which are cost-effective, pollution-free but have the uncertainty in the generations due to variation in windspeed and solar irradiance. There are few studies related to integration of RERs into ORPD. Biswas [26], presented success-history differential evolution (SHADE-EC) algorithm for solving the single and multi-objective stochastic ORPD with the integration of the RERs using IEEE30 and IEEE57 standards. The appropriate PDF functions are taken into consideration to model stochastic power generation and load from RERs at different scenarios. The implementation of feasible solution search with PSO algorithm is discussed by Marcela Martinez-Rojas [27]. The ORPD on PCC is considered to minimize the power losses in a windfarm. A lightning attachment procedure optimization was introduced by Ramadan [28]. The paper explained the uncertainty of the wind speed and the solar irradiance which are modeled using Weibull PDF and Lognormal PDF to reduce the power losses of IEEE30 standard at different 25 scenarios. Mohseni-Bonab [29-30] formulated the multi-objective stochastic problem related to ORPD considering the uncertainty of load, and it was tested on IEEE14 and IEEE118 standards.

The traditional PSO algorithm is typically facing with sub-optimal problem and caught into the local minima. While, traditional GSA has required a lengthy computational time for solving some optimization issues to find the global solution. PSO has a propensity of quick convergence in a multi variable optimization problem while the global exploration performance of GSA is mostly conspicuous. Hence, PSO and GSA algorithms have their individual perspectives and encourage us to develop an effectual hybridization technique of PSOGSA algorithm to overcome the weakness of the existed traditional PSO and GSA algorithms [24].

The fractional calculus (FC) is a strong mathematical tool that attracts the attentions of the most researchers and implemented in the field of science and technology, for example, electromagnetism, robotics, electronics, physics, telecommunication and control systems [31-34] but it is not yet much explored in the field of ORPD with the integration of RERs. By using the FC concept, the fractional properties are applied to update the velocity of traditional PSOGSA algorithm to obtain the fractional FPSOGSA that aims to enhance the convergence performance of the algorithm and memory effects of all past events [25].

The stochastic ORPD problem is taken as a single or multi objective problem with integration of uncertainty load demand, solar irradiance and wind speed. The research is using the single objective approach and ORPD problem with uncertainty is solved in load demand, solar irradiance and windspeed by using the scenario-based approach in order to optimize the power losses, voltage stability index and voltage deviation.

The objective of this research is to implement the novel FPSOGSA algorithm for ORPD with integration of RERs for reducing the power losses, voltage deviation as well as improving the voltage stability index.

From the comprehensive literature review, the few research gaps are observed and discussed as follows.

- ORPD without RERs is simply solved by FPSOGSA algorithm and the uncertainty of solar irradiance, wind speed and load demand at different scenarios is not considered.
- ORPD containing uncertainties of RERs was not tested based on IEEE30 standards with 13 control variables [26,28].
- The voltage stability index was not discussed in [26,28] for the scenario-based approach.

The salient features of the research can be summarized as below:

- The novel FPSOGSA approach was implemented to the ORPD with RERs according to IEEE30 standard using 13 and 19 control variables.
- The mathematical model of ORPD was built under the uncertainties of load demand, solar and wind power on IEEE 30-bus system.
- Solving ORPD for reducing power losses and voltage deviations as well as improving voltage stability by applying FPSOGSA algorithm with and without integration of RERs.
- The outcomes of FPSOGSA was analyzed and compared with those of the different meta-heuristic techniques for ORPD.

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In organizing rest of the article, section II describes the problem formulation. Section III presents the mathematical model with the uncertainty in load demand, solar PV unit and wind power for ORPD. Section IV explains the mathematical models of PSO, GSA, PSOGSA, FC with graphical abstract. Section V explains the result and discussion while Section VI is the conclusion section.

II. PROBLEM FORMULATION

The first objective of solving ORPD is to find the best control parameter settings to diminish the power losses. ORPD is assigned as follows.

$$\begin{gathered} Min\ Obj_f(r,s) \\ Subject\ To: \\ g_q(r,s)=0 \quad j=1,2,3,...,m \\ h_n(r,s)=0 \quad n=1,2,3,...,\ p \end{gathered} \tag{1}$$

Where, h_n and g_q are the inequality and the equality constraints while r and s are the control and state variables.

$$\begin{gathered} r=[V_{g,1}...V_{g,NPV},Q_1...Q_{NPV},T_{p,1}...T_{p,NTr}] \\ s=[P_1,V_1...V_{NPQ},Q_{g,1}...Q_{g,NPV},S_{t,1}...S_{t,R}] \end{gathered} \tag{2}$$

Where, V_g denotes the generator voltage, Q_C denotes reactive power of the compensator, T_p is the transformer tap, P_1 is the slack bus power, V is the load bus voltage, Q_g is the reactive power of the generator, S_t is apparent power flow in the transmission line. While, *R*, *NPV*, *NTr* and *NPQ* represent the numbers of generators, transformer taps, load buses and transmission lines.

A. Objective Functions

There are three minimization objectives of ORPD and related details are discussed in below sub-sections.

1) POWER LOESSES

$$F_1=Ploss=\sum_{i=1}^{R}G_{ij}(V_i^2+V_j^2-2V_iV_j\cos\delta_{ij}) \tag{3}$$

Where, $Ploss$ denotes the reactive power loss and G_{ij} denotes the conductance of the transmission line. While, the inequality constraints are given for generators, transformers, shunt VAR compensators and security. Where, max and min are superscripts of the maximum and minimum limit of the control and dependent variables. The equality constraint is representing as follows:

$$\begin{aligned} &P_{\min,gk}\le P_{gk}\le P_{\max,gk} && k=1,2,3,...,NPV \\ &Q_{\min,gk}\le Q_{gk}\le Q_{\max,gk} && k=1,2,3,...,NPV \\ &V_{\min,gk}\le V_{gk}\le V_{\max,gk} && k=1,2,3,...,NPV \\ &T_{\min,n}\le T_n\le T_{\max,n} && k=1,2,3,...,NTr \\ &Q_{\min,cn}\le Q_{cn}\le Q_{\max,cn} && k=1,2,3,...,NBr \\ &S_{\ln}\le S_{\max,ln} && k=1,2,3,...,NPV \\ &V_{\min,n}\le V_n\le V_{\max,n} && k=1,2,3,...,NPV \end{aligned} \tag{4}$$

$$\begin{cases} P_{g,i}-P_{d,i}=|V_i|\sum_{i=1}^{R}|V_j|(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}) \\ Q_{g,i}-Q_{d,i}=|V_i|\sum_{i=1}^{R}|V_j|(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}) \end{cases} \tag{5}$$

While, the penalty factor is representing as the given mathematical expression.

$$\begin{gathered} Obj_f=F_1/F_2/F_3+k_1(P_{g,i}-P_{g,i}^{\lim})^2+ \\ k_2\sum_{i=1}^{NPV}\left(Q_{g,i}-Q_{g,i}^{\lim}\right)^2+k_3\sum_{i=1}^{NPQ}\left(V_{L,i}-V_{L,i}^{\lim}\right)^2 \\ +k_3\sum_{i=1}^{NBr}\left(S_{L,i}-S_{L,i}^{\lim}\right)^2 \end{gathered} \tag{6}$$

2) VOLTAGE DEVIATION

It sets another objective to improve the voltage profile in the electrical grid, the following expression is used to measure the voltage deviation (VD).

$$F_2=\min VD=\left(\sum_{p=1}^{Nl}|V_{lp}-1|\right) \tag{7}$$

3) VOLTAGE STABILITY

In the electric power networks, the instability of the voltages is considered as the most critical phenomena which leads to the voltage collapse steadily or immediately. In the improvement of voltage stability, the minimization of voltage stability factor is denoted as L-index of each bus. It can be improved by alleviating the L-index values at one bus and formulated as follows.

$$F_3=\min L_i=\left|1-\frac{\sum_{j=1}^{Ng}y_{ij}v_j}{v_i}\right| \quad i=1,2,......N_{Bus} \tag{8}$$

$$F_3=\min\ L_{\max} \quad i=1,2,....,N_{Bus} \tag{9}$$

Here, L_i denotes the stability index value of bus *i,* while y_{ij} represents the mutual admittance between bus *i* and *j*.

III. UNCERTAINTY MODEL OF RERs

A. MODEL OF LOAD UNCERTAINTY

The load uncertainty can be represented by the normal PDF function that is formulated by the following expression [30].

$$\Delta d(L_d)=\frac{1}{\rho_d\sqrt{2\pi}}\exp\left[-\frac{(L_d-\omega_d)^2}{2\rho_d{}^2}\right] \tag{10}$$

Where, L_d represents normal probability distribution function (PDF), ω_d and ρ_d are the mean and standard deviations with the values 10 and 70, respectively [28].

B. MODEL OF WIND POWER

The wind speed is varying continuously and stochastically which causes the uncertainty in power system. This means that the solution cannot be presented as a certain point of the wind speed and the uncertain characteristics of the wind speed should be considered. Commonly, the Weibull PDF (11) is used to cultivate the wind power.

$$W(v_v)=\left(\frac{\beta}{\alpha}\right)\left(\frac{v_v}{\alpha}\right)^{\beta-1}\exp\left[-\left(\frac{v_v}{\alpha}\right)^{\beta}\right] \quad 0\le v_v\le\infty \tag{11}$$

$$P_{Wt}(v_v)=\begin{cases} 0 & for \quad v_v\le v_{v,i}\ \&\ v_v\le v_v \\ P_{Wr}\left(\dfrac{v_v-v_{v,i}}{v_{v,r}-v_{v,i}}\right) & for \quad v_{v,i}\le v_v\le v_{v,r} \\ P_{Wr} & for \quad v_{v,r}\le v_v\le v_{v,o} \end{cases} \tag{12}$$

Where, $W(v_v)$ represents the PDF of wind speed v_v, α and β refer to the scale and shape parameters of Weibull function, P_{Wt} represents the rated power generated by the wind turbine while $v_{v,i}$, $v_{v,r}$ and $v_{v,o}$ denote the cut-in, rated and cut-out wind speed, and their parameters with limits are given in Table I [25]. The active and reactive generated powers of the wind farm are depicted as follows.

$$\begin{cases} P_{Wf} = P_{Wt}\times N_{Wt} \\ Q_{Wf} = \dfrac{P_{Wf}}{\cos\phi}\sqrt{1-\cos\phi} \end{cases} \tag{13}$$

Where, P_{Wt} and Q_{Wf} represent the active and the reactive power generated by the windfarm while N_{Wt} represents the number of the wind turbines connected in a windfarm.

C. MODEL OF SOLAR POWER

The output of the solar PV units also fluctuates due to variation of the solar irradiance daily and seasonally which leads to the change in power system. For optimal planning, the uncertain characteristics of the solar irradiance should be considered. Commonly, lognormal PDF function is used to describe the solar irradiance (W/m^2). The mathematical expression is given as follows.

$$\Delta\rho(g_s)=\frac{1}{g_s\sigma_s\sqrt{2\pi}}\exp\left[-\frac{(\ln(g_s)-\mu_s)^2}{2\sigma_s^{\,2}}\right] \quad g_s\ge 0 \tag{14}$$

$$P_s(g_s)=\begin{cases} P_{Sr}\left(\dfrac{g_s^{\,2}}{g_{std}\times X_c}\right) & for \quad 0\le g_s\le X_c \\ P_{Sr}\left(\dfrac{g_s}{g_{std}}\right) & for \quad g_s\ge X_c \end{cases} \tag{15}$$

Where, $\Delta\rho(g_s)$ represents the probability density of the solar irradiance in (W/m^2), σ_s and μ_s denote the standard and mean deviation, P_{Sr} is the generated power by PV, X_c is the irradiance point while g_{std} is the solar environment solar irradiance and their limit values are given in Table II [28].

The wind and solar powers are mainly affecting the dispatch solution of ORPD. The integrated mathematical expression of ORPD containing windfarm and PV is given as follows.

$$\begin{cases} P_{g,i}+P_{Wf}+P_s=P_{d,i}+|V_i|\sum\limits_{i=1}^{R}|V_j|(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}) \\ Q_{g,i}+Q_{Wf}+Q_s+=Q_{d,i}+|V_i|\sum\limits_{i=1}^{R}|V_j|(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}) \end{cases} \tag{16}$$

It should be highlighted here that Eq. (16) represents the balanced power flow in system considering the renewable energy resources where the generated active or reactive powers from the conventional power sources ($P_{g,i}$, $Q_{g,i}$) add the generated powers from the solar PV (P_s, Q_s) and the windfarm (P_{Wf}, Q_{Wf}) on condition that the load demands ($P_{d,i}$, $Q_{d,i}$) and the power losses in the system must be covered.

D. EXPECTED SUM OF OBJECTIVE FUNCTIONS

In case of the uncertainty in the power system, several scenarios will be taken into account. Thus, the losses, the voltage deviations and the stability index should be assigned in these scenarios which are known as the expected values. To find the expected sum of the power losses (E_{Ploss}), the given expression is used as follows.

$$E_{Ploss}=\sum_{sc=1}^{Nsc}\Delta_{sc}\times P_{losses,sc} \tag{17}$$

Where, Nsc denotes the total number of the generated scenarios, Δ_{sc} is the probability of the given scenarios while $P_{losses,sc}$ represents the power losses of each scenario. Similarly, to find the expected sum of voltage deviation, the expression is used as follows.

$$E_{VD}=\sum_{sc=1}^{Nsc}\Delta_{sc}\times VD_{sc} \tag{18}$$

Where, E_{VD} represents the sum of the expected voltage deviation in the given scenarios while VD_{sc} represents the voltage deviation of each scenario. Likewise, the expected sum of voltage stability index is formulated by the following expression.

$$E_{VSI} = \sum_{sc=1}^{Nsc} \Delta_{sc} \times VSI_{sc} \tag{19}$$

Where, E_{VSI} is the expected sum of voltage stability index while VSI_{sc} is the voltage stability index of each scenario.

IV. METHODOLOGY

A. PARTICLE SWARM OPTIMIZATION (PSO)

The traditional PSO algorithm was proposed by Kennedy and Eberhart in 1995 [35] where the solution is considered as a particle. The representation of the position and velocity are given as follows.

$$\begin{gathered} v_{i,t+1} = w \times v_{i,t} + c2 \times r1\left(P_{BST} - X_{i,t}\right) + c2 \times r1\left(G_{BST} - X_{i,t}\right) \\ x_{i,t+1} = v_{i,t} + v_{i,t+1} \end{gathered} \tag{20}$$

Where, $v_{i,t+1}$ denotes the velocity of the i^{th} particle at given iteration (t+1) while $x_{i,t+1}$ denotes its position, w represents the inertia weight, $r1$ and $r2$ denote random values in range [0,1], $c1$ and $c2$ are the coefficient for P_{BST} and G_{BST} positions, and w is the inertia parameter that achieves better stability and it is given as follows.

$$w = w_i^{\max} - \frac{w_i^{\max} - w_i^{\min}}{iteration_i^{\max}} \times iteration \tag{21}$$

Where, $w_i^{\max}$ and $w_i^{\min}$ are the inertia values of the start and end of iterations.

B. GRAVITATIONAL SEARCH ALGORITHM (GSA)

GSA is presented by Rashedi in 2009 [36]. The algorithm is conceptualized from the Newton's Law where the collection of agents having masses accommodate to the fitness objective value. The initial number of agents are expressed as follows.

$$X_{\text{i}} = (x_i^1 \ldots x_i^{\text{dm}} \ldots x_i^n) \quad for\ i = 1,2,3,\ldots,N \tag{22}$$

Where, x_i^{dm} is the position of the i^{th} agent while the worst and best for each agent at each iteration is expressed as follows.

$$B_{bst}(t) = {}_{j\in\{1,\ldots m\}}^{\min}\ fit_j(t) \tag{23}$$

$$W_{wrst}(t) = {}_{j\in\{1,\ldots m\}}^{\max}\ fit_j(t) \tag{24}$$

Where, G_{const} at t^{th} iteration is given in Eq. (25), T represents the total iteration while G_{e} and α values are set to 1 and 23, respectively.

$$G_{const}(t) = G_e \times e^{-\alpha t/T} \tag{25}$$

The gravitational and the inertial masses are calculated as follows.

$$M_{at,i} = M_{pv,i} = M_{im,i} = M_i \qquad i = 1,2,3,\ldots,N \tag{26}$$

$$m_i(t) = \frac{fit_i(t) - W_{wrst}(t)}{B_{bst}(t) - W_{wrst}(t)} \tag{27}$$

$$m_i(t) = M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{28}$$

In the search space, overall acting forces on the agent is computed as follows.

$$F_i^{\text{dm}}(t) = \sum_{j=1, j\neq 1}^{N} rand_j(t) \times F_{ij}^{\text{dm}}(t) \tag{29}$$

Where, F_i^{dm} signifies the gravitational force applied from j^{th} to i^{th} agent at the explicit time computed as follows.

$$\begin{gathered} F_{ij}^{\text{dm}}(t) = G_{const}(t) \times \frac{M_{pv,i}(t) \times M_{at,j}(t)}{R_{ij}(t) + \in} \times \\ \left(x_j^{\text{dim}}(t) - x_i^{\text{dm}}(t)\right) \end{gathered} \tag{30}$$

The acceleration of an agent at the d^{th} dimension is computed as follows.

$$ac_i^{\text{dm}}(t) = \frac{F_i^{\text{dm}}}{M_{im,i}(t)} \tag{31}$$

The velocity and position of the traditional GSA are calculated by the following equations.

$$v_i^t(t+1) = rand_i \times v_i^{\text{dm}}(t) + ac_i^{\text{dm}}(t) \tag{32}$$

$$x_i^{\text{dm}}(t+1) = x_i^t(t) + v_i^{\text{dm}}(t+1) \tag{33}$$

C. PARTICLE SWARM OPTIMIZATION AND GRAVITATIONAL SEARCH ALGORITHM (PSOGSA)

The novel hybrid PSOGSA algorithm was firstly introduced by Mirjalili [25], the hybridization of PSO and GSA algorithms aims to enhance the seaching capabilities of these algorithms. Both algorithms are hybridized at low-level co-evolutionary heterogenous.

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$$
\begin{aligned}
v_i^{t+1} = w_{\text{in}ertia} \times v_i^t + c_1' \times rand_{i,1} \times ac_i^t + \\
c_2' \times rand_{i,2} \times (G_{BEST} - x_i^t)
\end{aligned} \quad (34)
$$

The position of particles are updated as follows.

$$
x_i^{t+1} = x_i^t + v_i^{t+1} \quad (35)
$$

E. FRACTIONAL CALCULUS

The FC concept plays an important role in the fields of mathematics, science, and technologies. Past few years, the researchers are using this mathematical tool for enhancing the performance of the algorithms applied in different fields, such as controllability, edge detection, stability, filtering, pattern recognition, identification and observability. In the literature, there are numerous different interpretations of FC, e.g. Grünwald-Letnikov interpretation signal $x(t)$ is expressed as follows [34].

$$
D^{\alpha}\left[x(t)\right] = \lim_{h \to o} \left[\frac{1}{h} \sum_{k=0}^{+\infty} \frac{(-1)^q \Gamma(\alpha+1) x(t-qh)}{\Gamma(q+1)\Gamma(\alpha-q+1)} \right] \quad (36)
$$

Γ represents the Euler gamma function.

$$
\Gamma(q) = (q-1)! \quad (37)
$$

Generally, a simple integer order only involves a finite series while Grünwald–Letnikov interpretation using fractional derivatives needs a number of infinite series. The fractional derivatives of Grünwald–Letnikov has the oblique memory effect of entire past events that will be reduced over the time. While, the discrete time interpolation of $D^{\alpha}\left(x[t]\right)$ is given using (38).

$$
D^{\alpha}\left(x[t]\right) = \frac{1}{T^{\alpha}} \sum_{k=0}^{r} \frac{(-1)^q \Gamma[\alpha+1] x[k-qT]}{\Gamma(q+1)\Gamma(\alpha-q+1)} \quad (38)
$$

Where, T is the sampling time, α is fractional order, Γ is Euler gamma function, q is the index which represents number of terms in power series expansion, and r is the truncation order. The velocity in (39) is modified to amend the velocity as follows.

$$
\begin{aligned}
v_{k+1}^n = v_k^n + \rho_1 r_1 (P_{BEST,i} - v_k^n) + \\
\rho_2 r_2 (G_{BEST} - v_k^n)
\end{aligned} \quad (39)
$$

$$
\begin{aligned}
v_{k+1}^n - v_k^n = \rho_1 r_1 (P_{BEST,i} - v_k^n) + \\
\rho_2 r_2 (G_{BEST} - v_k^n)
\end{aligned} \quad (40)
$$

$$
\begin{aligned}
v_{k+1}^n = -\sum_{k=1}^{r} \frac{(-1)^q \Gamma[\alpha+1] x[k+1-qT]}{\Gamma(q+1)\Gamma(\alpha-q+1)} + \\
\rho_1 r_1 (P_{BEST,i} - v_k^n) + \rho_2 r_2 (G_{BEST} - v_k^n)
\end{aligned} \quad (41)
$$

Where, r_1 and r_2 are the random numbers between [0,1], ρ_1 and ρ_2 are the local and global coefficients, n is particle index crossponding velocity v, while $P_{BEST,i}$ and G_{BEST} are the local and global positions.

The velocity order (α) could be a real number in [0,1] that learns the fractional optimization behavior of this novel mechanism, the fractional testing are between $a=0$ and $\alpha = 1$ with incrementation of steps $\Delta\alpha=0.1$. Thus, using $r = 4$, the updated velocity is represented as follows [42].

$$
\begin{aligned}
v_{k+1}^n = \alpha v_k^n + \frac{1}{2}\alpha(1-\alpha) v_{k-1}^n + \\
\frac{1}{6}\alpha(1-\alpha)(2-\alpha) v_{k-2}^n + \\
\frac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha) v_{k-3}^n + \\
\rho_1 r_1 (P_{BEST,i} - v_k^n) + \rho_2 r_2 (G_{BEST} - v_k^n)
\end{aligned} \quad (42)
$$

While the velocity of FPSOGSA is updated, Eq. (34) and (42) will be used as follows.

$$
\begin{aligned}
v_{k+1}^n = \alpha v_k^n + \frac{1}{2}\alpha(1-\alpha) v_{k-1}^n + \\
\frac{1}{6}\alpha(1-\alpha)(2-\alpha) v_{k-2}^n + \\
\frac{1}{24}\alpha(1-\alpha)(2-\alpha)(3-\alpha) v_{k-3}^n + \\
c_1' \times rand_{i,1} \times ac_i^t + c_2' \times rand_{i,2} \times (G_{BEST} - x_i^t)
\end{aligned} \quad (43)
$$

The steps of FPSOGSA for solving the ORPD including RERs is depicted in Fig. 1.

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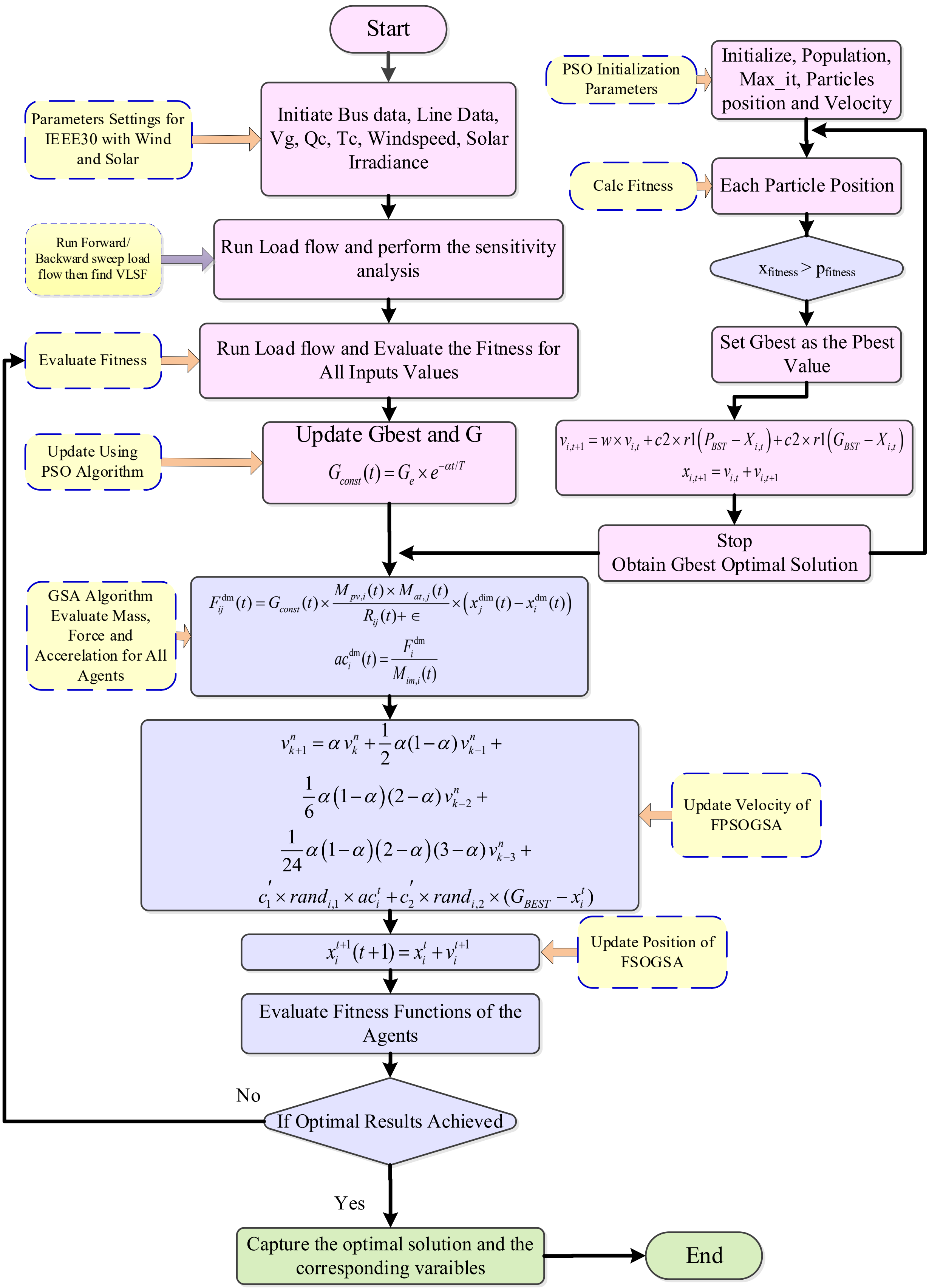

FIGURE 1. **Graphical Abstract of FPSOGSA Algorithm to ORPD Problem including RERs**

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V. RESULTS AND DISCUSSION

In this section, FPSOGSA is applied for solving ORPD with and without integration of RERs in order to optimize three objectives including power losses and voltage deviations reduction and improvement of voltage stability. The proposed algorithm is test on IEEE30 standard bus system. The IEEE30 standard bus system contains 41 branches, 30 buses, 6 generators, 4 transformers with 9 shunt VAR reactive compensators [51]. 19 control variables are considered for 9 shunt VAR compensators while 13 control variables are considered for 3 shunt VAR compensators based on IEEE 30-bus standard [25]. The simulations are carried on Core I5 PC and the FPSOGSA code for ORPD was programmed. For studying ORPD with RERs, the solar and wind powers resources have been considered as depicted in Fig. 2 where a wind farm is connected to the bus 5 while the solar power plant is injected to bus 8. The rated power of the wind farm is 75 MW where it consists of 25 wind turbines, each wind turbine capacity is about 3 MW. The selected parameters of a windfarm are given in Table I [26], [28]. Table II lists the parameters of the solar power PV plants which are connected to the generator bus 8 and its rated power is 50 MW. The parameters of FPSOGSA including number of particles, number of iterations, velocity bounds, size of population, fractional coefficient, cognitive/social acceleration, and inertia weight are given in Table III. The selection of fractional order depends upon the information of the optimization problem, experimentations with experience and extensive care [25], [39], [41]. The learning convergence curves of FPSOGSA algorithm are obtained at fractional order $\boldsymbol{\alpha = 0.6}$, population size 50, iteration 100 for all given objectives with and without integration of RERs while, the control parameter values for the generator voltages, shunt VAR reactive compensators and transformer tap are taken as given in Table IV.

A. ORPD PROBLEM WITHOUT RERs

The FPSOGSA algorithm is successfully applied on IEEE30 bus standard to minimize three objectives without integration of RERs including the power losses and voltage deviations reduction and voltage stability enhancement. The FPSOGSA simulation outcomes are given for IEEE30 with 13 and 19 control variable settings.

Tables V and VII shows the best control values for the $Ploss$ minimization, VD minimization and VSI enhancement for IEEE30 with 13 and 19 control variables, respectively. Table IX and Table X show the obtained results by application of different optimization algorithms, respectively. In case of minimizing the power losses for 13 control variables, the $Ploss$ by using FPSOGSA is reduced from 5.811 MW (base case) to 4.5308 MW. Judging from Table IX, the percentage reduction of losses is reported as: MFO is 19.01%, C-PSO is 17.37%, GWO is 18.80%, FODPSO is 18.67%, MICA-IWO is 14.43% and FODPSO-EE is 20.88%. In case of minimizing the power losses for 19 control variables, the power loss is reduced from 5.663 MW (base case) to 4.4952 MW by application of FPSOGSA. Judging from Table X, the

TABLE I
PARAMETERS OF WINDFARM GENERATOR CONNECTED AT BUS 5 IN IEEE30 STANDARD BUS SYSTEM [26]

Windfarm Specification: Turbine Model- Enercon E82-E4							
Windfarm	Rated Power	No. of Turbines	Each Turbine Power	Weibull Parameters	Cut-In (m/sec)	Rated (m/sec)	Cut-out (m/sec)
1 at bus 5	75 MW	25	3 MW	α=9, β=2	3	16	25

TABLE II
PARAMETERS OF SOLAR POWER GENERATOR CONNECTED AT BUS 8 IN IEEE30 STANDARD BUS SYSTEM [26]

Solar Power (PV)				
Solar Power	Rated Power (MW)	Standard Solar Irradiance (W/m^2)	Certain Irradiance Point (W/m^2)	Lognormal Parameters
1 at bus 8	50	1000	120	μs=5.5, σs=0.5

TABLE III
PARAMETERS SELECTION OF FPSOGSA ALGORITHM FOR ORPD PROBLEM WITH AND WITHOUT RES [39]

Description	Power Losses (MW)	Voltage Deviation (p.u)	Voltage Stability Index (p.u)
No. of Population	50	50	50
No. of Iterations	100	100	100
Local Acceleration Factor (LAF)	0.9-0.1	0.9-0.1	0.9-0.1
Global Acceleration Factor (GAF)	0.1-0.9	0.1-0.9	0.1-0.9
Inertia Weight	0.9-0.2	0.9-0.2	0.9-0.2
Fractional Order	α=0.6	α=0.6	α=0.6

TABLE IV
CONTROL VARIABLE SETTINGS FOR IEEE30 WITH 13 AND 19 VARIABLES WITH AND WITHOUT RERS [28]

IEEE30	Control Variables Settings for all Given Objectives		
13, 19 VAR	Vg	0.95	1.1
	Qc	0	0.050
	Tc	0.95	1.1

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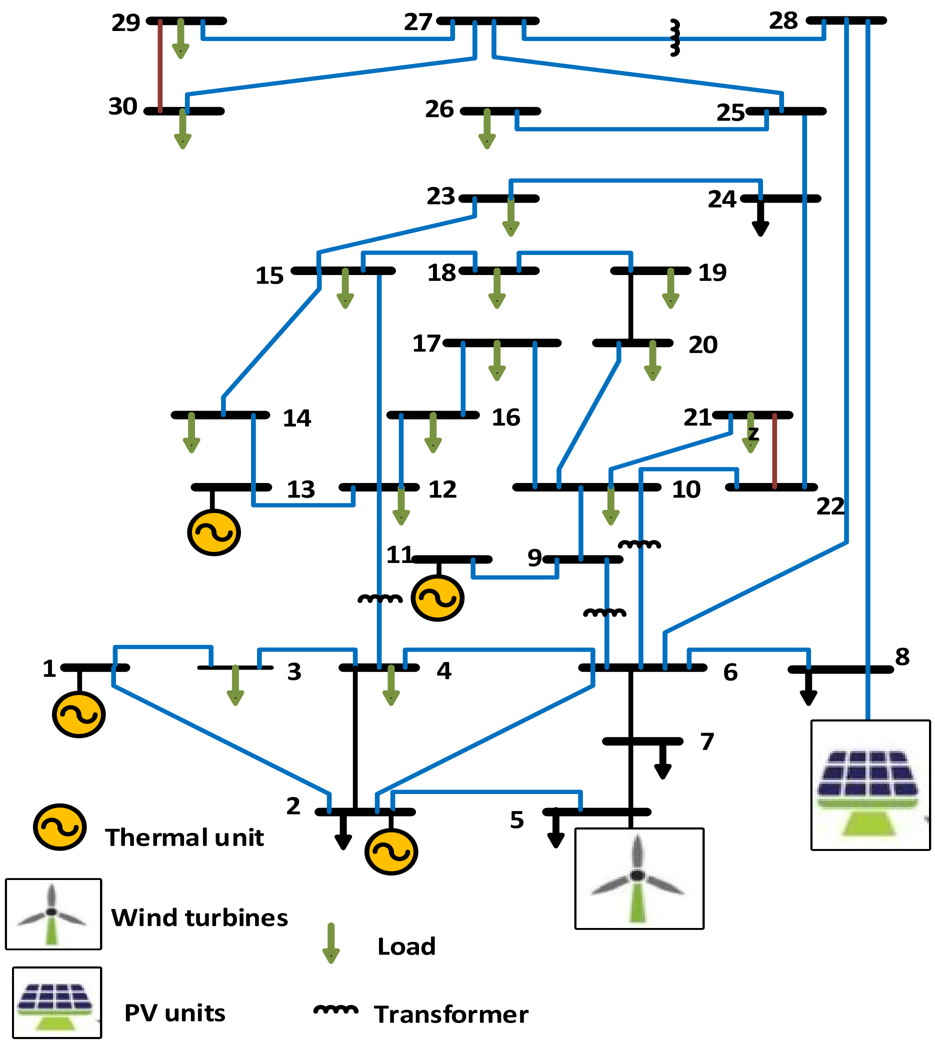

FIGURE 2. **Modified IEEE30-Bus System Including RERs**

percentage of losses are reported as: PSO-CF is 22.12%, QOTLBO is 21.54%, MFO is 22.34%, ALO is 21.01%, GWO is 20.21%, CLPSO is 21.50%, OGSA is 22.59%, PSOGSA is 22.03%, MSFS is 22.31%, LAPO is 19.85%, and the proposed algorithm is reported to 22.64%.

It is depicted that the outcomes obtained from the proposed FPSOGSA are less compared to the base case and other meta-heuristic approaches which endorsed the best performance of FPSOGSA. The Figs. 3 (a) and (b) demonstrated the best performance achieved by the proposed algorithm. The minimization of power losses for 13 and 19 variables is 4.5308 MW and 4.4952 MW, respectively. Figs. 4 (a) and (b) is for minimization of VD that obtained by FPSOGSA for 13 and 19 control variables which is 0.1060 p.u. and 0.0923 p.u., respectively. In addition, Figs. 5 (a) and (b) demonstrated the best convergence characteristics achieved by the proposed algorithm for minimization of VSI with 13 and 19 control variables which is 0.0953 p.u. and 0.0878 p.u., respectively. Figs. 3, 4 and 5 illustrates the trend of the objective functions versus iterations.

Judging from Table IX and Table X, the results computed by FPSOGSA are better than MFO [44], C-PSO [37], GWO [40], PSO-CF [23], QOTLBO [41], IGA [43], MICA-IWO [38], PSOGSA [45], FODPSO-EE [50], LAPO [28], ALO [42], MSFS [46], BBO [48] and OGSA [49].

According to Figs. 4, 5 and 6, FPSOGSA has the stable convergence capacity for given objectives without considering RERs. While, the estimation time of simulation are given in Tables V and VII. In addition, the dependent variables of ORPD i.e., reactive power outputs of non-considering RERs and the voltages of the load buses are given in Table VI and VIII for IEEE30 standard with both 13 and 19 control variables. The result shows that the dependent variables are remained within their permissible limits and there is no violation.

B. ORPD PROBLEM WITH UNCERTAINTY OF RERs

In this section, ORPD is solved using FPSOGSA with RERs. With the uncertainties of the load, solar irradiance and the wind speed, voltage deviations and the expected stability index according to (17), (18) and (19). Table XI shows the percentage load demands for each scenario and the output powers from the 25 scenarios can be obtained. The objective function is minimizing the expected power loss, the expected

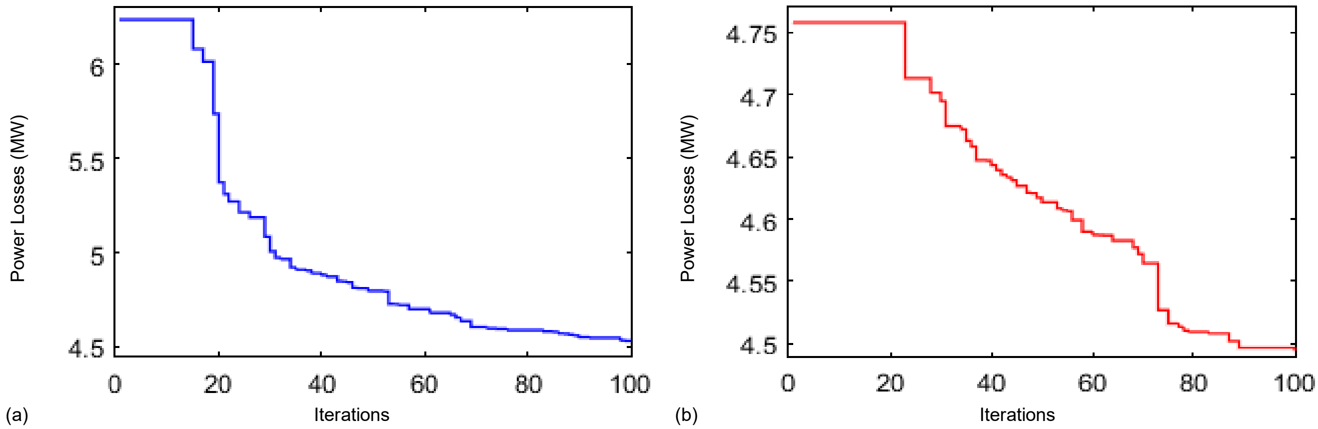

FIGURE 3. **Evolution of Power Losses (MW) of IEEE30 Bus Standard. (a) 13 Variables (b) 19 Variables**

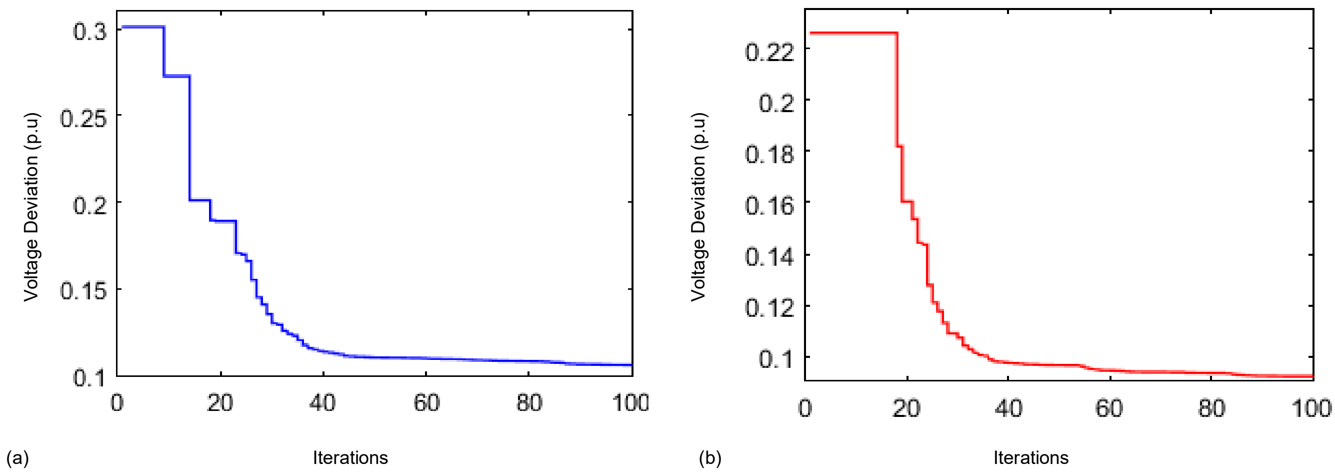

FIGURE 4. **Evolution of Voltage Deviation (p.u) of IEEE30 Bus Standard. (a) 13 Variables (b) 19 Variables**

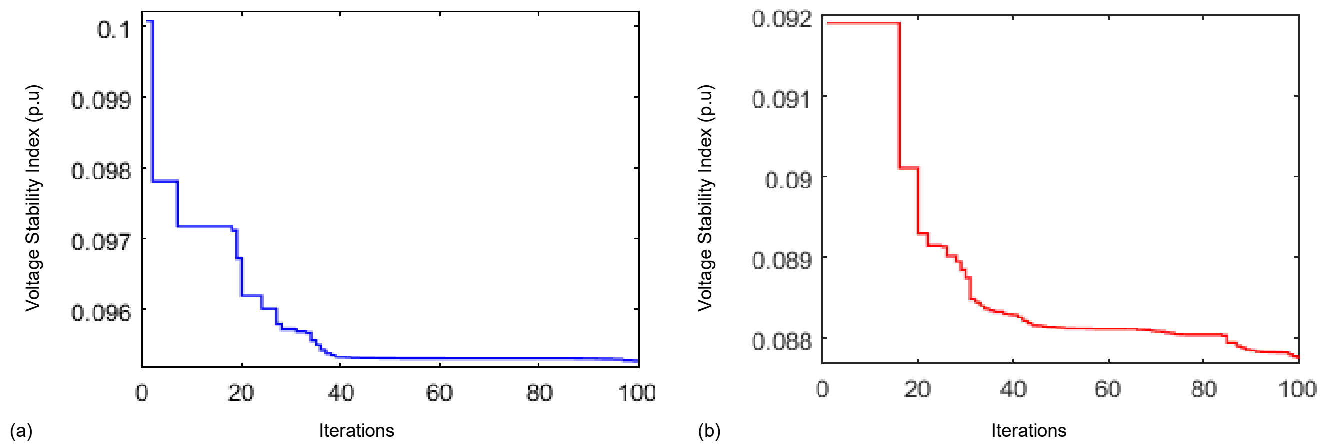

FIGURE 5. **Evolution of Voltage Stability Index (p.u) of IEEE30 Bus Standard. (a) 13 Variables (b) 19 Variables**

wind farm and the PV plant as well as the corresponding probabilities. The total expected values of the power loss, the voltage deviations and stability index without incorporating RERs are reported as 4.7985 MW, 0.7229 p.u., 0.1114 p.u., respectively, for IEEE30 with 13 control variables. Table XII shows the obtained results with RERs including the $Ploss$, VD and VSI for each scenario in case of 13 and 19 control variables.

As ORPD with 13 control variables is resolved, E_{Ploss} is reduced from 4.7985 MW to 2.2462 MW (53.19 %), E_{VD} is reduced from 0.7229 p.u to 0.1126 p.u (84.42 %), and E_{VSI} is reduced from 0.1114 p.u to 0.0952 p.u. (14.54%). When ORPD with 19 control variables is resolved, the E_{Ploss} is reduced from 4.7985 MW to 2.1782 MW (54.61 %), E_{VD} is reduced from 0.7229 p.u to 0.0840 p.u (88.38 %) and E_{VSI} is reduced from 0.1114 p.u to 0.0870 p.u. (21.90 %). The

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simulation time (sec) for IEEE30 with 13 and 19 control variables considering RERs are given in Table XII.

From the aforementioned results, inclusion of RERs can enhance the performance of the system considerably. Referring to Table XII, values of the $Ploss$, VD and VSI are changed according to variations of load demand, solar irradiance and the wind speed. the highest values of the $Ploss$, VD and VSI are obtained in the 1st and 7th scenarios where in the 1st scenario, the percentage load is high (105.784 %) and there is no output power from the wind farm, while in the 7th scenario, the output power from the wind farm and PV plant are small and the load is high.

VI. CONCLUSION

In the article, a novel heuristic approach of Fractional PSOGSA algorithm has been successfully implemented and applied to ORPD with and without RERs (Wind + PV) in the electrical systems. The uncertainties in RERs is considered by varying the windspeed, solar irradiance, the load demand by applying the Weibull and thee Lognormal probability distribution functions.

- The proposed algorithm is successfully applied to IEEE30 bus standard with 13 and 19 control variables to minimize the three objective functions, such as power losses, voltage deviation and voltage stability index.
- The overall results of FPSOGSA algorithm shows the better performance for ORPD problem with and without RERs as compared to the other heuristic approaches.
- The integration of FC into PSOGSA enhances the overall convergence strength with memory effect of the algorithm.

In future, FC will be added to other heuristic approaches for improvement.

TABLE V
CONTROL VARIABLE FOR POWER LOSSES, VOLTAGE DEVIATION AND VOLTAGE STABILITY INDEX WITHOUT RERS FOR IEEE30 STANDARD (13 VARIABLES)

Control Variables	$Ploss$ minimization	VD minimization	VSI enhancement
VG 1(p.u.)	1.0716	1.0330	0.9703
VG 2(p.u.)	1.0635	0.9983	1.0755
VG 5(p.u.)	1.0343	1.0151	1.0607
VG 8(p.u.)	1.0441	1.0047	1.0384
VG 11(p.u.)	0.9929	1.0297	1.0999
VG 13(p.u.)	1.0160	1.0110	1.0658
TC 6-9(p.u.)	0.9451	1.0287	1.0479
TC 6-10(p.u.)	1.0040	0.9055	0.9283
TC 4-12(p.u.)	0.9992	0.9498	1.0713
TC 27-28(p.u.)	0.9543	0.9518	0.9653
QC 3(p.u.)	0.0131	0.0498	0.0500
QC 10(p.u.)	0.0500	0.0500	0.0500
QC 24(p.u.)	0.0267	0.0500	0.0478
min F_1, F_2, F_3	4.5308 (MW)	0.1060 (p.u.)	0.0953 (p.u.)
Time (sec)	33.29	43.28	49.85

TABLE VI
DEPENDED VARIABLES FOR POWER LOSSES, VOLTAGE DEVIATION AND VOLTAGE STABILITY INDEX WITHOUT RERS FOR IEEE30 STANDARD (13 VARIABLES)

Depended Variables	Minimum Limits	Maximum Limits	$Ploss$ minimization	VD minimization	VSI enhancement
V_3(p.u.)	0.9	1.1	1.081	1.081	1.089
V_4(p.u.)	0.9	1.1	1.076	1.073	1.083
V_6(p.u.)	0.9	1.1	1.070	1.072	1.075
V_7(p.u.)	0.9	1.1	1.064	1.064	1.066
V_9(p.u.)	0.9	1.1	1.095	1.075	1.057
V_{10}(p.u.)	0.9	1.1	1.073	1.080	1.051
V_{12}(p.u.)	0.9	1.1	1.078	1.094	1.039
V_{14}(p.u.)	0.9	1.1	1.065	1.080	1.028
V_{15}(p.u.)	0.9	1.1	1.061	1.076	1.027
V_{16}(p.u.)	0.9	1.1	1.069	1.081	1.037
V_{17}(p.u.)	0.9	1.1	1.066	1.075	1.041
V_{18}(p.u.)	0.9	1.1	1.053	1.066	1.023
V_{19}(p.u.)	0.9	1.1	1.052	1.063	1.024
V_{20}(p.u.)	0.9	1.1	1.056	1.066	1.030
V_{21}(p.u.)	0.9	1.1	1.062	1.070	1.040
V_{22}(p.u.)	0.9	1.1	1.062	1.071	1.041
V_{23}(p.u.)	0.9	1.1	1.055	1.069	1.026
V_{24}(p.u.)	0.9	1.1	1.054	1.067	1.033

V_{25}(p.u.)	0.9	1.1	1.066	1.076	1.050
V_{26}(p.u.)	0.9	1.1	1.050	1.060	1.033
V_{27}(p.u.)	0.9	1.1	1.082	1.090	1.068
V_{28}(p.u.)	0.9	1.1	1.066	1.068	1.069
V_{29}(p.u.)	0.9	1.1	1.064	1.072	1.050
V_{30}(p.u.)	0.9	1.1	1.053	1.061	1.039
Q_{G1}(MVA_R)	-20	150	-8.54	-7.95	-12.73
Q_{G2}(MVA_R)	-20.0	60.0	15.79	16.69	8.72
Q_{G5}(MVA_R)	-15.0	62.5	23.43	22.75	21.03
Q_{G8}(MVA_R)	-15.0	48.7	48.02	44.08	35.28
Q_{G11}(MVA_R)	-10.0	40.0	3.17	13.57	23.30
Q_{G13}(MVA_R)	-15.0	44.7	17.71	4.87	20.84

TABLE VII
CONTROL VARIABLE FOR POWER LOSSES, VOLTAGE DEVIATION AND VOLTAGE STABILITY INDEX WITHOUT RERS FOR IEEE30 STANDARD (19 VARIABLES)

Control Variables	$Ploss$ minimization	VD minimization	VSI enhancement
VG 1(p.u.)	1.0455	1.0686	0.9719
VG 2(p.u.)	1.0389	0.9504	0.9629
VG 5(p.u.)	1.0116	1.0189	0.9557
VG 8(p.u.)	1.0180	1.0071	1.0743
VG 11(p.u.)	0.9740	1.0681	0.9524
VG 13(p.u.)	1.0845	0.9769	1.0877
TC6-9(p.u.)	0.9578	1.0828	0.9000
TC 6-10(p.u.)	0.9007	0.9078	1.0679
TC 4-12(p.u.)	1.0083	0.9158	1.0081
TC 27-28(p.u.)	0.9534	0.9792	0.9784
QC 10(p.u.)	0.0037	0.0297	0.0495
QC 12(p.u.)	0.0208	0.0179	0.0500
QC 15(p.u.)	0.0113	0.0188	0.0494
QC 17(p.u.)	0.0308	0.0229	0.0351
QC 20(p.u.)	0.0438	0.0500	0.0447
QC 21(p.u.)	0.0423	0.0469	0.0305
QC 23(p.u.)	0.0297	0.0496	0.0500
QC 24(p.u.)	0.0000	0.0500	0.0495
QC 29(p.u.)	0.0387	0.0415	0.0490
min F_1, F_2, F_3	4.4952 (MW)	0.0923 (p.u.)	0.0878 (p.u.)
Time (sec)	42.46	43.29	50.60

TABLE VIII
DEPENDED VARIABLES VALUES FOR POWER LOSSES, VOLTAGE DEVIATION AND VOLTAGE STABILITY INDEX WITHOUT RERS FOR IEEE30 STANDARD (19 VARIABLES)

Depended Variables	Minimum Limits	Maximum Limits	$Ploss$ minimization	VD minimization	VSI enhancement
V_3(p.u.)	0.9	1.1	1.083	1.078	1.083
V_4(p.u.)	0.9	1.1	1.078	1.071	1.076
V_6(p.u.)	0.9	1.1	1.071	1.075	1.071
V_7(p.u.)	0.9	1.1	1.064	1.066	1.064
V_9(p.u.)	0.9	1.1	1.104	1.064	1.085
V_{10}(p.u.)	0.9	1.1	1.100	1.083	1.022
V_{12}(p.u.)	0.9	1.1	1.087	1.110	1.055
V_{14}(p.u.)	0.9	1.1	1.078	1.097	1.043
V_{15}(p.u.)	0.9	1.1	1.079	1.093	1.041
V_{16}(p.u.)	0.9	1.1	1.087	1.093	1.035
V_{17}(p.u.)	0.9	1.1	1.093	1.083	1.023
V_{18}(p.u.)	0.9	1.1	1.078	1.082	1.026
V_{19}(p.u.)	0.9	1.1	1.081	1.079	1.019
V_{20}(p.u.)	0.9	1.1	1.087	1.082	1.022
V_{21}(p.u.)	0.9	1.1	1.090	1.077	1.016
V_{22}(p.u.)	0.9	1.1	1.090	1.078	1.018
V_{23}(p.u.)	0.9	1.1	1.078	1.089	1.037
V_{24}(p.u.)	0.9	1.1	1.077	1.077	1.025
V_{25}(p.u.)	0.9	1.1	1.089	1.079	1.047
V_{26}(p.u.)	0.9	1.1	1.072	1.063	1.030
V_{27}(p.u.)	0.9	1.1	1.104	1.089	1.069
V_{28}(p.u.)	0.9	1.1	1.069	1.073	1.068
V_{29}(p.u.)	0.9	1.1	1.099	1.084	1.065
V_{30}(p.u.)	0.9	1.1	1.083	1.068	1.048
Q_{G1}(MVA_R)	-20	150	-9.67	-6.65	-9.20
Q_{G2}(MVA_R)	-20.0	60.0	14.15	16.06	15.49
Q_{G5}(MVA_R)	-15.0	62.5	23.23	21.18	23.05

Q_{G8}(MVA_R)	-15.0	48.7	45.78	33.82	45.26
Q_{G11}(MVA_R)	-10.0	40.0	-1.83	19.48	8.42
Q_{G13}(MVA_R)	-15.0	44.7	10.17	-7.47	8.34

TABLE IX
COMPARISON OF DIFFERENT ALGORITHM WITH FPSOGSA FOR MINIMIZATION OF DIFFERENT OBJECTIVE FUNCTIONS OF IEEE30 (13 CONTROL VARIABLES)

Algorithm	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$	Algorithm	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$
MFO [44]	4.5865	0.12154	n/a	FODPSO [39]	4.606	n/a	n/a
C-PSO [37]	4.6801	n/a	n/a	MICA-IWO [38]	4.846	n/a	n/a
GWO [40]	4.5984	0.12604	n/a	FODPSO-EE [50]	4.5971	n/a	n/a

TABLE X
COMPARISON OF DIFFERENT ALGORITHM WITH FPSOGSA FOR MINIMIZE OBJECTIVE FUNCTIONS OF IEEE30 STANDARD (19 CONTROL VARIABLES)

Algorithm	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$	Algorithm	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$
PSO-CF [23]	4.5258	0.1287	0.1261	CLPSO [47]	4.5615	0.4773	n/a
QOTLBO [41]	4.5594	n/a	0.1242	OGSA [49]	4.4984	n/a	0.1407
MFO [44]	4.5128	2.0316	n/a	PSOGSA [45]	4.5309	2.05504	n/a
IGA [43]	n/a	n/a	0.1807	MSFS [46]	4.5143	n/a	n/a
ALO [42]	4.5900	n/a	0.1307	BBO [48]	n/a	0.0926	n/a
GWO [20]	4.5185	0.1325	0.1125	LAPO [28]	4.5389	n/a	n/a

TABLE XI
SUMMARY OF DIFFERENT SCENARIOS FOR WIND AND SOLAR POWER

Scenarios	Solar Irradiance Gs (W/m2)	Wind (m/sec)	PS (MW)	PW (MW)	Percentage % Loading Pd	Scenarios Probability
1	1115.95	1.702	50	0	105.784	0.001
2	726.973	7.605	36.3486	26.5773	55.714	0.001
3	476.09	10.414	23.8045	42.7731	73.165	0.007
4	803.282	2.377	40.1641	0	77.665	0.001
5	935.904	9.182	46.7952	35.6654	99.491	0.001
6	607.269	3.158	30.3635	0.9115	60.573	0.004
7	365.655	5.712	18.2827	15.6462	97.292	0.001
8	326.471	9.221	16.3236	35.8904	58.378	0.038
9	0	8.166	16.3236	29.8038	98.092	0.006
10	751.597	5.47	37.5799	14.2500	77.942	0.002
11	181.466	4.661	9.0733	9.5827	41.386	0.004
12	869.125	5.871	43.4563	16.5635	65.615	0.001
13	441.341	8.806	22.0670	33.4962	90.475	0.003
14	1103.501	10.001	50	40.3904	66.773	0.001
15	551.278	8.628	27.5639	32.4692	61.498	0.009
16	0	6.229	27.5639	18.6288	68.935	0.478
17	138.834	9.084	6.9417	35.1000	67.603	0.093
18	379.832	9.678	18.9916	38.5269	71.77	0.044
19	672.788	5.271	33.6394	13.1019	79.921	0.004
20	411.201	7.88	20.5601	28.1538	72.351	0.037
21	201.152	4.813	10.0576	10.4596	78.322	0.048
22	95.657	11.743	3.8126	50.4404	66.073	0.027
23	229.271	2.538	11.4635	0	74.465	0.071
24	518.084	3.245	25.9042	1.4135	63.754	0.012
25	275.124	14.439	13.7562	65.9942	67.487	0.106

TABLE XII
FINAL RESULTS OF EXPECTED PLOSSES (MW), VD (P.U) AND VSI (P.U) AT DIFFERENT SCENARIOS WITH INTEGRATION OF RERS (WIND AND SOLAR POWER)

Scenarios	IEEE30 (13 Variables)			IEEE30 (19 Variables)		
	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$	$Ploss(MW)$	$VD(p.u)$	$VSI(p.u)$
1	8.9531	0.2167	0.1425	8.8609	0.2097	0.1355
2	1.0336	0.1147	0.0785	0.9747	0.0910	0.0694
3	1.6932	0.1155	0.0998	1.6248	0.0840	0.0918
4	3.8160	0.1230	0.1054	3.7437	0.0973	0.0977
5	4.5015	0.1873	0.1339	4.4178	0.1772	0.1268
6	2.0245	0.1112	0.0843	1.9609	0.0860	0.0756
7	7.4276	0.1876	0.1311	7.3391	0.1785	0.1240

8	1.0769	0.1119	0.0817	1.0150	0.0875	0.0728
9	6.4599	0.1895	0.1322	6.3720	0.1804	0.1251
10	3.0238	0.1233	0.1058	2.9522	0.0973	0.0981
11	0.9282	0.1325	0.0624	0.8716	0.1142	0.0515
12	1.6398	0.1100	0.0904	1.5763	0.0827	0.0820
13	4.3424	0.1606	0.1220	4.2617	0.1459	0.1147
14	1.1733	0.1101	0.0918	1.1113	0.0824	0.0835
15	1.1476	0.1109	0.0854	1.0853	0.0856	0.0768
16	2.0745	0.1097	0.0945	2.0074	0.0800	0.0863
17	1.9168	0.1088	0.0929	1.8488	0.0791	0.0847
18	1.8238	0.1137	0.0981	1.7553	0.0823	0.0900
19	3.4914	0.1283	0.1083	3.4179	0.1053	0.1007
20	2.2095	0.1145	0.0988	2.1401	0.0834	0.0908
21	4.4994	0.1270	0.1064	4.4233	0.1049	0.0987
22	1.5153	0.1081	0.0910	1.4488	0.0798	0.0827
23	4.5328	0.1192	0.1015	4.4586	0.0916	0.0936
24	2.3973	0.1094	0.0882	2.3315	0.0827	0.0797
25	1.2414	0.1093	0.0927	1.1763	0.0803	0.0845
Expected Sum	2.2462(MW)	0.1126(p.u.)	0.0952(p.u.)	2.1782(MW)	0.0841(p.u.)	0.0870(p.u.)
Times (sec)	38.70	40.92	48.23	42.49	40.21	48.91

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