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Application of Shannon Entropy Implementation Into A Novel Fractional Particle Swarm Optimization Gravitational Search Algorithm (FPSOGSA) for Optimal Reactive Power Dispatch Problem

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ABSTRACT Optimal reactive power dispatch (ORPD) intended for reducing the real power losses of the transmission scheme remains one of the supreme concerns for the research community to explore the competence of power schemes. Numerous systems have been deliberate to increase the performance of the optimization method in tunning the operational variables as well as explored through estimating the final results. The research offering a novel approach based on the entropy evolution technique implemented into Fractional PSOGSA algorithm to solve the optimal reactive power dispatch problem. To alleviate the drawback of PSOGSA the fractional and entropy techniques are implemented into the algorithm which enhanced memory effect, stability and robustness of the algorithm. The novel design of FPSOGSA-Entropy is further tested for the optimal reactive power dispatch problems on IEEE-30 and IEEE-57 bus standards to find the two objective functions; minimization of power line losses and voltage deviation. The superior performance of the proposed FPSOGSA-Entropy is further verified with the results of simple FPSOGSA for both single and multiple runs through comparative analysis study with state of art counterparts for each scenario of optimal reactive power dispatch problems.

INDEX TERMS Optimal power flow (OPF), optimal reactive power dispatch (ORPD), particle swarm optimization (PSO), gravitational search algorithm (GSA), fractional calculus (FC).

NOMENCLATURE

$\mathrm{F}_1, \mathrm{F}_2$	Objective functions
P^i_{Gn}, P^i_{Dn}	Real Power Generation and Demand
Q^i_{Gn}, Q^i_{Dn}	Reactive Power Generation and Demand
G_{ij}, B_{ij}	Conductance and Susceptance
Nlb, Nt	No. of load buses and transmission lines
$\mathrm{P}_{\mathrm{Vge,i}}, \mathrm{P}_{\mathrm{Tc,i}}, \mathrm{P}_{\mathrm{Grp,i}}$	Penalty Factors
$\mathrm{M}_{\mathrm{ps,i}}(\mathrm{t}), \mathrm{M}_{\mathrm{ac,j}}(\mathrm{t})$	Active and Passive gravitational masses of agents
G(t)	Gravitational Constant at time t
$\mathrm{N}_{\mathrm{t}}, \mathrm{N}_{\mathrm{Qc}}, \mathrm{N}_{\mathrm{g}}$	No. of transformers, compensators, generators
$-\beta, \ \alpha$	Descending Coefficient, Fractional order
G_{0}	Initial Value
$\mathrm{M}_{\mathrm{ii}}(\mathrm{t})$	Mass of object i
ac_{i}	Accerlation of agent i
$\mathrm{V}_{\mathrm{i}}, \mathrm{V}^{\mathrm{su}}_{\mathrm{i}}$	Voltages at ith bus, Specified Value range [0,1]

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I. INTRODUCTION

A. MOTIVATION AND INCITEMENTS

The electrical power system is usually an intricate network that contains three step of power supply to variety of load demand such as; generation, transmission networks and distributions. It is projected to utilize it at the minimum consumption of resources and giving the reliability and security. In the recent research and developments, the field of optimal reactive power dispatch attained the attraction of the researcher interest due to its capability to security and economic operation in power networks. It is one of the basic sub non-linear problem of the optimal power flow that contains both continues and discrete variables related to equality and inequality constraints. The best setting of the variables provides the good economic operation and it can be achieved by adjusting the control variables such as; voltages of generator buses, transformers tap settings and shunt reactive compensators.

B. LITERATURE REVIEW

The previous optimization used to solve the ORPD problems are such as; linear programming [1], quadratic programming [2], Newton's method [3], primal-dual algorithm-based interior point techniques [4] and gradient-based algorithm [5]. These techniques have some drawbacks such as accuracy loss and premature convergence. To resolve these problems, the new meta-heuristic on stochastic search-based approaches are introduced such as differential evolution, genetic algorithm, evolutionary programming and strategy and tabu search [6]–[10]. These schemes can capable of handling the non-convex and discontinuous of fitness function problem with finding the global minima.

The development and the exploitation in meta-heuristic approach are further exposed to improve the results while resolving the optimal reactive power dispatch problems (ORPD) such as; particle swarm optimization [11], harmony search algorithm [12], improved harmony search algorithm [13] gray wolf optimizer [14], cuckoo search algorithm [15], backtracking search algorithm [16], gravitational search algorithm [17], seeker optimization algorithm [18], gaussian bare-bones water cycle algorithm [19], colliding bodies optimization algorithm [20], chaotic krill herd algorithm [21], moth-flame algorithm [22], chaotic particle swarm optimization [23], bacterial colony chemotaxis algorithm [24], whale optimization algorithm [25], adaptive chaotic symbiotic organisms search algorithm [26], imperialist competitive algorithm [27], invasive weed optimization [28] and firefly algorithm [29]. Moreover, some other meta-heuristic approaches in support are discussed in [30]–[35]. All these optimization techniques have their value of importance, applications, impacts and their limitations to resolve the optimization issues of optimal reactive power dispatch.

The topical studies are investigated in scheming of meta-heuristics fractional evolutionary approaches by inspiring the concept of fractional calculus implies in the internal structure of the optimizer. For specimen, fractional particle swarm optimization FPSO and fractional order darwinian particle swarm optimization FODPSO [36] are observed the good optimization techniques. The applications of fractional concept are using in the different approaches such as; frequency control and automatic generation control [37], robotics [38], image processing [39], bioengineering [40], control systems [41], digital circuit synthesis [42], feature selection [43], adaptive extended Kalman filtering [44], design of PID controller [45] and extreme learning machine [46].

Over the year, there are several entropy interpretations have been proposed in which the best known are chaos spreading, information, disorder, mixing and freedom [47]. First of all, the description about entropy was given by Boltzmann to define the systems that changes from one ordered to disordered states. The spreading concept used by Guggenheim to specify the energy diffusion from small to a big volume. Lewis, in an isolated system the spontaneous expansion of gas, the uncertainty increases while the information regarding particles are decreases. Shannon, gives the information theory to enumerate the losses information during the transmission of a given message [48]. He also focused in statistical and physical restraints which limits the message of transmission. While, their application have been observed in different fields such as; feature extraction [49], identification [50], weighting analysis [51], frequency shifting and detection [52], image alignment [53], laser dynamics [54], gear fault diagnosis [55], structural pattern recognition [56], hydrologic synthesis [57], material selections [58] and measure of information [53].

C. PAPER CONTRIBUTION AND POWER ORGANITION

Optimal reactive power dispatch is a non-linear complex, non-convex, non-continuous and multi-model problem which involves discrete as well as continuous variables. Thus, its solution comprises of different objective functions like improving voltage profile, voltage stability, reducing power losses enhancement and transmission cost minimization. Thus, application the conventional particle swarm optimization may suffer from stagnation and it may be trapped in local optima as well as it does not have strongly convergence guarantees. While, GSA has good memory property but it required extensive time for some optimization problems to find the global solution. The main idea is to integrate both algorithms to get the exploitation / exploration abilities from PSO and GSA algorithm.

Aforementioned, the vast applications of fractional and entropy diversity concepts in field of science and technology. We can refer the integration of the fractional properties into the internal structure of PSOGSA algorithm to update velocity and developed the FPSOGSA algorithm. In addition, the Shannon entropy is implemented to the position of the FPSOGSA algorithm to developed the novel FPSOGSA entropy in order to enhance the convergence strength of the algorithm with improving the memory effects [41].

In this paper, the FPSOGSA-Entropy algorithm is proposed for enhancing the searching capabilities to be applied for solving the ORPD. The selection / updating process regarding particles are depended upon the change in the entropy. In the paper, FPSOGSA-Entropy algorithm is proposed for enhancing the searching capabilities to be applied for solving the ORPD.

The learning methods incorporated in the novel proposed FPSOGSA-Entropy algorithm are as follows:

- Novel application of fractional and entropy evolutionary techniques implemented and improved the optimization strength of FPSOGSA-Entropy for the optimal reactive dispatch problems.
- The proposed strategy is successfully applied to the optimal reactive power dispatch problems to find the minimization of power line losses with voltage deviation.
- The performance of the algorithm is determined through the outcomes of proposed FPSOGSA-Entropy over simple FPSOGSA algorithm through the statistical analysis in term of stairs, histogram, empirical CDF, minimization curves and box plots gauges.

This paper proposes the utilization concept related to a novel meta-heuristic approach based on FPSOGSA-Entropy algorithm to solve the optimal reactive power dispatch problems. In order to find the two objective functions of minimization of power line losses and voltage deviation, the special tool of MATPOWER is used to run the power flow [28]. The paper organization is set as follows: Section 2 computational problem formulation of optimal reactive power dispatch, Section 3 gives a mathematical review of traditional PSO, GSA, fractional calculus, Entropy evolution technique and graphical explanation with pseudo code, Section 4 explores the result and discussion, Section 5 represents the comparison of statistical analysis between FPSOGSA-Entropy and simple FPSOGSA algorithm while Section 6 states the conclusion.

II. SYSTEM MODEL: ORPD PROBLEM

The optimal reactive power dispatch is a sub problem of optimal power flow that delivers the optimal standards of control variables through reducing a predefined objective function with respect to the operational constraints of the scheme. The objectives of ORPD for two objective functions are formulated as follows [59].

Generally, the function $f\ (x,\ y)$ describes as the objective function, x is represented as vector of dependent variables while y is indicated as the vector of control variables.

$$\begin{aligned} g(x,y) &= 0 \\ h(x,y) &\leq 0 \end{aligned} \tag{1}$$

where $g(x,y) = 0$ represents the equality constraints including the balance active and reactive powers flow in system while $h(x,y) \leq 0$ represents the inequality constraints including the dependent and the control variables such as the generator voltages, the transformer taps, the reactive power of the generators, the voltage of load buses.

A. OBJECTIVE FUNCTION 1 (MIN PLOSS (X, Y))

F_1 is the objective function which aims to minimize the entire power line losses.

$$F_1 = P_{loss}(x, y) = \sum_{i=lb}^{Nt} P_{loss} \tag{2}$$

The power balance of load flow equation for equality constraints are given as follows:

$$P^i_{Gn} - P^i_{Dn} = V_i \sum_{j \in N_i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \tag{3}$$

$$Q^i_{Gn} - Q^i_{Dn} = V_i \sum_{j \in N_i} V_j (B_{ij} \cos\theta_{ij} + G_{ij} \sin\theta_{ij}) \tag{4}$$

The inequality constraints are considered for generators, the constraints are generator real as well as reactive power generation limits and voltage limits are given as follows:

$$\begin{aligned} P^{min}_{G,i} &\leq P_{G,i} \leq P^{max}_{G,i} \quad i = 1, 2.....N_g \\ Q^{min}_{G,i} &\leq Q_{G,i} \leq Q^{max}_{G,i} \quad i = 1, 2.....N_g \\ V^{min}_{G,i} &\leq V_{G,i} \leq V^{max}_{G,i} \quad i = 1, 2.....N_g \end{aligned} \tag{5}$$

The formulation of the transformer tap setting is restricted by their lower upper limits and defined as follows:

$$T^{min}_{t,i} \leq T_{t,i} \leq T^{max}_{t,i} \quad i = 1, 2 \ldots\ldots, N_t \tag{6}$$

whereas, the minimum and the maximum limits of the shunt reactive compensators are given as follows:

$$Q^{min}_{c,i} \leq Q_{c,i} \leq Q^{max}_{c,i} \quad i = 1, \ldots\ldots\ldots N_{Qc} \tag{7}$$

In optimal RPD, the inequality constraints are defined as the following penalty factor equation.

$$\begin{aligned} F_P = f(F_1/F_2) &+ \sum_{i \in Nqp} P_{Vge,i} \left(V_i - V^{lim}_i\right)^2 \\ &+ \sum_{i \in N_T} P_{Tc,i} \left(T_i - T^{lim}_i\right)^2 + \sum_{i \in N_G} P_{Grp,i} \left(Q_i - Q^{lim}_i\right)^2 \end{aligned} \tag{8}$$

here, x^{lim} is the limit values of the dependent variable x, so the representation for V^{lim}_i, T^{lim}_i and Q^{lim}_i are as follows.

If $x > x^{max}$, then $x^{lim} = x^{max}$
elseif $x > x^{min}$, then $x^{lim} = x^{min}$
else
$x^{lim} = x$
end

B. OBJECTIVE FUNCTION 2 (VOLTAGE DEVIATION)

F_2 is the second objective function which aims to minimize the voltage deviation.

$$F_2 = VD(x, y) = \sum_{i=1}^{Nlb} \left[V_i - V^{su}_i\right] \tag{9}$$

III. METHODOLOGY

The proposed strategy is based on FPSOGSA-Entropy to solve the optimal reactive power dispatch problem tested on IEEE 30 and 57 Standards with 13, 19 and 25 control variables respectively. The design approach of is given in the following steps:

- A Brief review on PSO, GSA, FC and Shannon Entropy
- The graphical illustration of overall workflow of FPSOGSA-Entropy in Fig. 1.
- The Algorithm. 1 pseudocode of the proposed FPSOGSA-Entropy

A. PARTICLE SWARM OPTIMIZATION (PSO)

It is one of the most common computational method established by Eberhart and Kennedy in 1995 [60]. The algorithm is inspired by birds flocking, where the velocity is maintained by every bird while it closes to the food. By adding the velocity, the initial population will be improved and it determined the difference between the particles with respect to Pbest and Gbest. The updating of velocity v_i for every particle is given as follows.

$$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times (Pbest - x_i(t)) + c_2 \times rand \times (Gbest - x_i(t)) \tag{10}$$

here, w inertia weight, c_1, c_2 are the positive coefficients, Pbest and Gbest are the local and the global best position. While, the position x_i is updating as follows.

$$x_i(t+1) = x_i(t) + v_i(t) \tag{11}$$

B. GRAVITATIONAL SEARCH ALGORITHM (GSA)

It is the new stochastic search technique introduced by Rashedi *et al.* in 2009 [61] in which agents are measured due to performance on basis of their masses while the objects are attracted with each other with gravity force. Therefore, the gravity force leads to overall movement of entire objects towards other with heavier mases. Suppose, there are N number of agents in a system, GSA algorithm starts with the randomly placing entire agents in the search space. According to gravity law, the force applied on the i^{th} mass from j^{th} mass is defined as follows:

$$F_{ij,d}(t) = G(t)\frac{M_{ps,i}(t) \times M_{ac,j}(t)}{\| X_i(t), X_j(t) \|_2}(x_{i,d}(t) - x_{j,d}(t)) \tag{12}$$

here, G(t) is calculated as:

$$G(t) = G_0 \times \exp(-\beta \times iter/\max iter) \tag{13}$$

For the i^{th} agent, the total force wielded from other agents is defined as follows:

$$F_{i,d}(t) = \sum_{j \neq i} rand_j F_{ij,d}(t) \tag{14}$$

The acceleration of i^{th} agent is computed as follows:

$$a_{i,d}(t) = \frac{F_{i,d}(t)}{M_{ii}(t)} \tag{15}$$

here, the updating velocity and position of GSA are computed as follows:

$$v_{i,d}(t+1) = rand_i \times v_{i,d}(t) + a_{i,d}(t) \tag{16}$$

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t) \tag{17}$$

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

The optimal values are obtained with the motion of the agents in search space during hybridization process but perhaps their methods of movements are different. In GSA the movement of agent computed by the total forces applied from other agents. The GSA contains some draw backs such as; lacking of memory and only present position of the agent further acts of updating the agent's positions. While, the PSO uses kind of memory such as; best earlier position of each and among all particles; thus, speed increases towards the optimal solution during movement of individual particles. In this approach to enhance the performance of GSA by improving the memory and group information of PSO has been used.

here, the c'_1 and c'_2 are positive coefficient constants, $Pbest_i$ is the best previous position of i^{th} particle while *Gbest* represents the best previous position of all particles. The mathematical representation of the velocity and the positions are given as follows [62].

$$v_i(t+1) = w_f \times v_i(t) + c'_1 \times rand_{i,1} \times ac_i \times + c'_2 \times rand_{i,2} \times (G_{best}(t) - x_i(t)) \tag{18}$$

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t) \tag{19}$$

D. FRACTIONAL CALCULUS

The idea of fractional calculus (FC) plays a vital role in mathematical modeling for increasing the performance of algorithms applied to different fields for specimen; edge detection, observability, identification and robustness stability. The Euler gamma function is as follows.

$$\Gamma(k) = (k-1)! \tag{20}$$

The Grünwald–Letnikov [63] explanation of fractional differential with order $\alpha \in C$ is further explanation for discrete time interpolation of signal (x[t]) is defined as:

$$D^\alpha (x[t]) = \frac{1}{T^\alpha} \sum_{k=0}^{r} \frac{(-1)^k \Gamma[\alpha+1] x[t-kT]}{\Gamma(k+1)\Gamma(\alpha-k+1)} \tag{21}$$

here, k represents the index that represents number of terms in power series expansion in basic Grunwald-Letnikov interpretation of fractional calculus. T represent the sampling time, α is the fractional order, Γ represents Euler gamma function, while r is the truncation order. Whereas, the velocity is defined as follows:

$$v^n_{t+1} - v^n_t = \rho_1 r_1 (LB^n_t - x^n_t) + \rho_2 r_2 (GB^n_t - x^n_t) \tag{22}$$

Here, v^n_{t+1} indicates the next velocity at t^{th} iteration, x denotes particle position, n is the particle index crossponding velocity v, r1 and r2 are the random numbers range between [0,1],

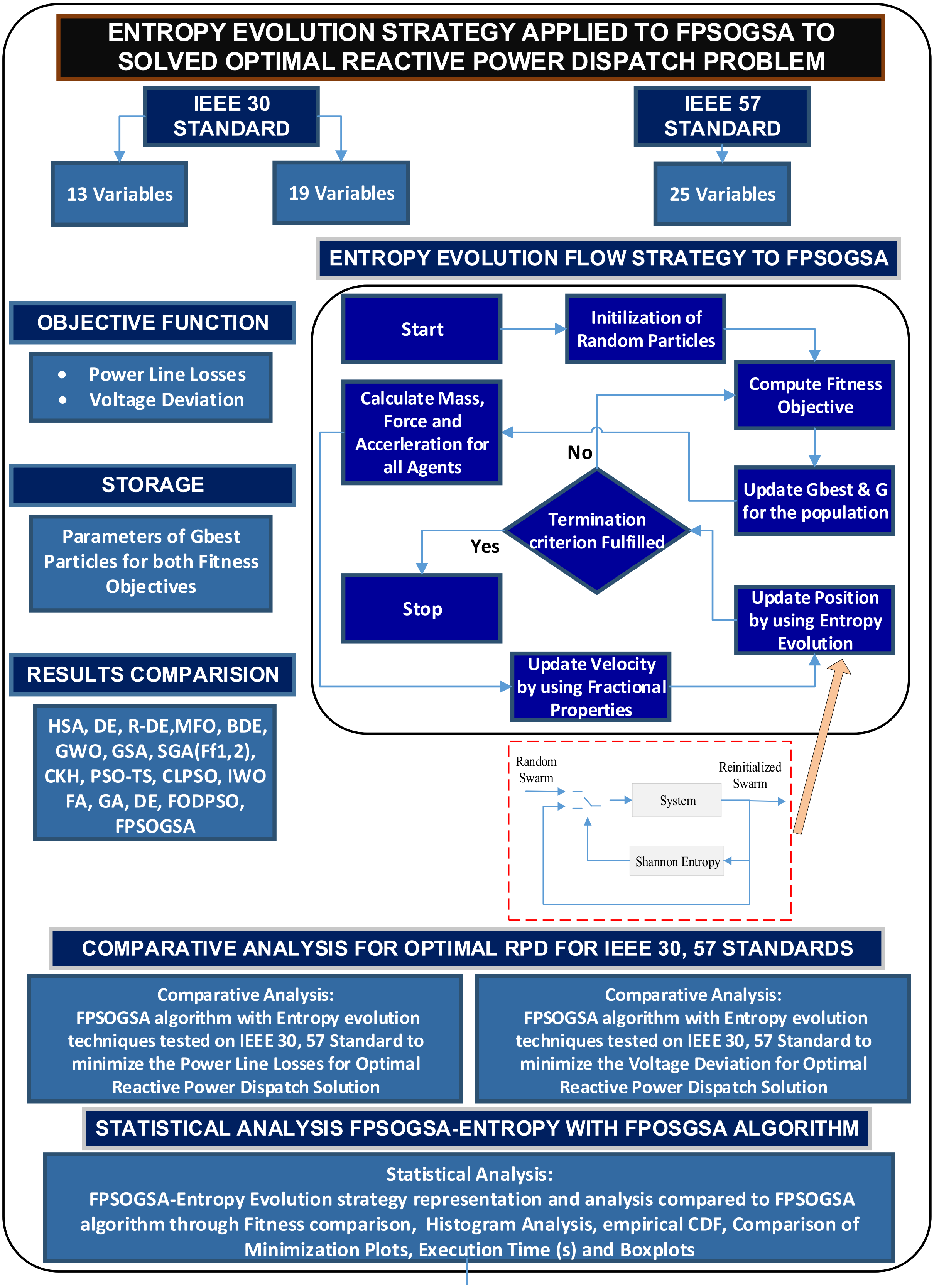

FIGURE 1. Graphical abstract of FPSOGSA-Entropy Algorithm tested on IEEE30 and 57 Standards for power losses minimization and voltage deviation.

Algorithm 1 Pseudocode of Designed FPSOGSA-Entropy for Solving ORPD Problems

Inputs: Set iterations, swarm size, fractional orders with control variables for tested IEEE-30, IEEE 57 Standards.
Output: Power Line losses (2) and Voltage deviation (9).
Start FPSOGSA-Entropy

Step 1: Initialization: Randomly generated swarms with n particles
Provide I/p to every particle according to IEEE Bus dimension
For every particle of swarm
For the dimension *based on variables*
Randomly set x and v with permissible real entries
End

Step 2: Evaluate fitness for each particle of Swarm using (2) and (9)
With run the power flow.

Step 3: Stop the execution of algorithm based on following factors
a) Total iterations executed
b) Saturation limit attains
If termination criteria fulfilled then go to step 5 and 6.

Step 4: Calculating Parameters: Performed by (12), (13) and (15)

Step 5: Updating Velocity: Updating velocity of FPSOGSA-Entropy by (24):

$$v(p,t+1) = \alpha\, v(p,t) + \frac{1}{2}\alpha(1-\alpha)\, v(p,t-1) + \frac{1}{6}\alpha\,(1-\alpha)\,(2-\alpha)\, v(p,t-2) + \frac{1}{24}\alpha\,(1-\alpha)\,(2-\alpha)\,(3-\alpha)\, v(p,t-3) + c_1' \times rand_{i,1} \times ac_i(p,t) + c_2' \times rand_{i,2} \times (G_{best}(p,t) - x_i(p,t))$$

Here, p denotes the particle, t is the flight index

Step 6: Updating Position: FPSOGSA-Entropy updating position by (28).

$$x(p,t+1) = x(p,t) + v(p,t+1)$$

Update particle of swarm and go to Step 2.

Step 7: Storage: Save parameters of Global best on minimization of transmission power losses and voltage deviation.

Step 8: Analysis: Repeat step 1 to step 5,6 for different fractional order alpha for detailed analysis of the results.

Step 9: Replication: Repeat the steps 1 to 6 for IEEE 30 and 57 Standards with 13, 19 and 25 control variables.

End FPSOGSA-Entropy

ρ_1 and ρ_2 are the local and global coefficients, while LB_t^n and GB_t^n are the local and global positions. By considering *T = 1* in (21), the (23) can rewrite and express as:

$$\mathrm{v}_{t+1}^{n} = -\sum_{k=1}^{r} \frac{(-1)^k \Gamma\,[\alpha+1]\; \mathrm{v}_n^s\,[t+1-kT]}{\Gamma(k+1)\Gamma(\alpha-k+1)} + \rho_1 r_1(\mathrm{LB}_t^n - x_t^n) + \rho_2 r_2(\mathrm{GB}_t^n - x_t^n) \tag{23}$$

The order of velocity order derived in between the real number of limitations $0 \le \alpha \le 1$ and for the consideration of the fractional concept, it increases the memory with leading to a smoother variation. The behavior of the curve for fractional mechanism testing on FPSOGSA algorithm is range between $\Delta\alpha = 0$ to $\alpha = 1$ by stepping of $\Delta\alpha = 0.1$ increment. The updated velocity in case of using fractional properties added into PSOGSA (18) is rewritten as follows.

$$v_{t+1}^n = \alpha\, v_t^n + \frac{1}{2}\alpha(1-\alpha)v_{t-1}^n + \frac{1}{6}\alpha\,(1-\alpha)\,(2-\alpha)\, v_{t-2}^n + \frac{1}{24}\alpha\,(1-\alpha)\,(2-\alpha)\,(3-\alpha)\, v_{t-3}^n + c_1' \times rand_{i,1} \times ac_i(t) + c_2' \times rand_{i,2} \times (G_{best}(t) - x_i(t)) \tag{24}$$

E. SHANNON ENTROPY

The Shannon, gives the information theory to enumerate the losses information during the transmission of a given message [48]. The concept of entropy evolutionary techniques implemented for increasing the performance of the algorithm in the fields are feature extraction, identification, weighting analysis, structural pattern recognition, hydrologic synthesis and measure of information. The mathematical expression of the Shannon entropy equation is given as follows:

here, H is defined as the measure of choice, information and uncertainty.

$$H(X) = -K \sum_{x\varepsilon X} p_{i-th}(x) \log p_{i-th}(x) \tag{25}$$

here, K is the positive constant, frequently its value is set to 1. The above expression considered a discrete random variables $x\varepsilon X$ characterized by probability distribution $p(x)$.

$$H(X,Y) = -K \sum_{x\in X} \sum_{y\in Y} p_{i-th}(x,y) \log p_{i-th}(x,y) \tag{26}$$

The above expression is the extended form of Shannon entropy to the random multivariable.

F. SHANNON ENTROPY IMPLEMENTED TO FRACTIONAL PSOGSA ALGORITHM

The technique is used in the study is to encourage the exploitation and exploration the entropy during the Fractional PSOGSA time evolution in order to enhance the overall convergence of the algorithm. For this purpose, the concept of Shannon entropy is introduced in the internal structure of FPSOGSA algorithm to enhance the strength of the algorithm. The FPSOGSA is the non-deterministic approach, therefore a set of 100 autonomous trail is executed to represent the statistical data set.

Certainly, entropy measures the changing propensity of the system energy, for specimen; during the present case, the spreading of the particles inside the search space. Bearing the idea comes in mind, the distance d_{i-th} measured between i-th particle position and global best particle. So, the probability of every particle p_{i-th} is specified by the distance d_{i-th} to maximum possible distance $d_{max\,i}$. The computational relation is given as follows [59]:

$$p_{i-th} = \frac{d_{i-th}}{d_{max\,i}} \tag{27}$$

For, swarm size = n, and k = 1, the diversity index (28) is computed as follows:

$$H(X) = -\sum_{i=1}^{n} p_{i-th} \log p_{i-th} \tag{28}$$

The presented research work is motivated by the need to understand the entropy signal during the FPSOGSA time evolution and to use it for improving its convergence. The entropy signal is used to influence the algorithm behavior, namely the reinitialization of the swarm given in Fig. 1. Where the concept of Shannon entropy applied to the position of the FPSOGSA-Entropy algorithm to improve the convergence performance of the algorithm by updating the Gbest and G values of the algorithm.

TABLE 1. Parameters settings of FPSOGSA-Entropy Algorithm for IEEE 30 and 57 bus standards [72].

Parameters Settings	IEEE 30 (13 and 19 Variables)	IEEE57 (25 Variables)
Swarm Size	20	20
Iterations	50	50
Fractional Order (α)	0.1-0.9	0.1-0.9
Inertia Weight (ω)	0.9-1.3	0.9-1.3

IV. RESULTS AND DISCUSSION

In order to demonstrate the effectiveness of the proposed algorithm for solving optimal reactive power dispatch problems, MATLAB 2015 on Window 10 Professional Lenovo E-480 Model Intel®Core^{TM}i7-8550U CPU @ 1.80 GHz 8GB RAM is operated to performed the simulations. The paper represents the three cases of IEEE 30 (13 and 19 variables) and IEEE 57 (25 variables) standards with giving six scenarios are directed to prove the better efficiency of the proposed FPSOGSA-Entropy algorithm. The two objective functions are subjected to find such as; minimization of power line losses and voltage deviation. The detail of all scenarios are defined as follows:

1. Power Line Losses for IEEE 30 Standard (13 Var)
2. Voltage Deviation for IEEE 30 Standard (13 Var)
3. Power Line Losses for IEEE 30 Standard (19 Var)
4. Voltage Deviation for IEEE 30 Standard (19 Var)
5. Power Line Losses for IEEE 57 Standard (25 Var)
6. Voltage Deviation for IEEE 57 Standard (25 Var)

Additionally, the detail results of the proposed algorithm are compared to the other algorithms are given in Table 2, IV and VI while the statistical outcomes are compared to the variant of the proposed algorithm with FPSOGSA algorithms.

The performance of the FPSOGSA is highly sensitive to the values of its main controlling parameter and a small variation in these parameters may cause premature saturation that results in a suboptimal solution. The parameters of the FPSOGSA i.e., velocity bounds, number of flights, number of particles, size of swarm, inertia weight, social and cognitive acceleration vector and fractional coefficient are selected based on experience, knowledge of optimization problem, knowledge of the optimizer, experimentations, and extensive care.

The selection of parameters for tune up the proposed FPSOGSA-Entropy is given in Table 1 and in case of every scenario the algorithms is run for different fractional alpha order to attain the best performance of the proposed strategy. For all scenarios, the outcomes are reported and mapped into the same MATPOWER load flow (LF) package to evaluate the entire transmission loss with voltage deviation as for fair comparison with other selected optimization algorithms.

A. MINIMAZATION OF POWER LINE LOSSES TESTED ON IEEE 30 STANDARD (13 CONTROL VARIABLES)

The consideration of the control variables in the first scenario is 13 and it contains six generators connected at the buses 2, 5, 8, 11 and 13 while the slack bus is connected at bus 1,

TABLE 2. Optimal values of control variables for IEEE30 Standard (13 Var) for minimization power line losses.

Control Variables	HSA [12]	DE [64]	R-DE [28]	MFO [28]	GWO [66]	FODPSO-EE [65]	FPSOGSA [72]	FPSOGSA-Entropy
$V_{gt\,1}$	1.0726	1.095319	1.1	1.1	1.1000	1.1	1.1000	1.1000
$V_{gt\,2}$	1.0625	1.085946	1.0949	1.0946	1.0912	1.1	1.0945	1.0945
$V_{gt\,5}$	1.0399	1.062628	1.0707	1.0756	1.0715	1.0833	1.0752	1.0766
$V_{gt\,8}$	1.0422	1.065076	1.073	1.772	1.0759	1.08533	1.0771	1.0773
$V_{gt\,11}$	1.0318	1.0266	1.065	1.0868	1.1000	1.0931	1.1000	1.1000
$V_{gt\,13}$	1.0681	1.014253	1.0961	1.1	1.1000	1.1	1.1000	1.1000
$T_{c\,6\text{-}9}$	1.01	1.017796	1.05	1.04110	1.0408	1.0434	1.0417	1.0327
$T_{c\,6\text{-}10}$	1.00	0.979277	0.9	0.95007	0.9020	1.0294	0.9000	0.9001
$T_{c\,4\text{-}12}$	0.99	0.9797843	1.0	0.95541	0.9799	1.0752	0.9752	0.9666
$T_{c\,27\text{-}28}$	0.97	1.008938	0.97	0.95754	0.9719	1.0210	0.9650	0.9618
$Q_{c\,10}$	34	20.22359	0.01	7.1032	2.7566	4.2822	3.8974	7.5330
$Q_{c\,20}$	12	9.584327	0.26	30.796	2.9020	2.6762	4.7813	1.4159
$Q_{c\,24}$	10	13.02992	0.12	9.8981	1.7639	6.6747	4.7105	6.1373
P_{losses}, MW	5.109	4.888081	4.6675	4.608	4.5538	4.5971	4.5342	4.5323

TABLE 3. Comparison of percentage of power losses minimization for IEEE30 standard (13 variables).

Compared Results	Base Case	HSA [12]	DE [64]	R-DE [28]	MFO [28]	GWO [66]	FODPSO-EE [65]	FPSOGSA [72]	FPSOGSA-Entropy
Plosses, MW	5.663	5.109	4.888081	4.6675	4.608	4.5538	4.5971	4.5342	4.5323
% of losses	-	9.78	13.68	17.58	18.63	19.59	18.82	19.93	19.96

the range of the generators (V_{gt}) are between [0.95-1.1]. There are four transformers tap settings (T_c), which are placed at the given lines 6-9, 6-10, 4-12 and 28-27 and their variables the range is between [0.9-1.1]. Moreover, three shunt compensators are connected to the buses 10, 20 and 24 with the range between [0-30 MVAr]. The load demand for the current scenario is set in per unit as $S = P + jQ = 2.832 + j1.262$ pu [72].

The Table 2 disclosed the optimal outcomes from the different algorithms such as; HSA [12], DE [64], R-DE [28], MFO [28], GWO [66], FODPSO-EE [65], FPSOGSA [72] are compared to the proposed FPSOGSA-Entropy algorithm for optimal reactive power dispatch problem. The reduction in power line losses % are given in Table 3, the base case values is considering here 5.663 MW for comparing the results from different techniques. The power losses % in MW are reported such as; HSA is 9.78%, DE is 13.68%, R-DE is 17.58%, MFO is 18.63%, GWO is 19.59%, FODPSO-EE is 18.82%, FPSOGSA is 19.93% while the proposed FPOSGSA-Entropy is reported at 19.96% respectively.

The Fig. 2 illustrates the performance curve of proposed FPOSGSA-Entropy algorithm at the different fractional alpha orders range between $\alpha = [0.1, \ldots, 0.9]$ in case of finding the minimization of power line losses. The selection of the parameters in case of each fractional alpha order is set to 20 swarm, 50 iterations with 10 autonomous trails to find the lowermost losses at the best fractional alpha order.

After getting the results, the best fractional alpha order $\alpha = 0.7$ gives 4.5487 MW while the worst result is reported 4.6194 MW at $\alpha = 0.4$.

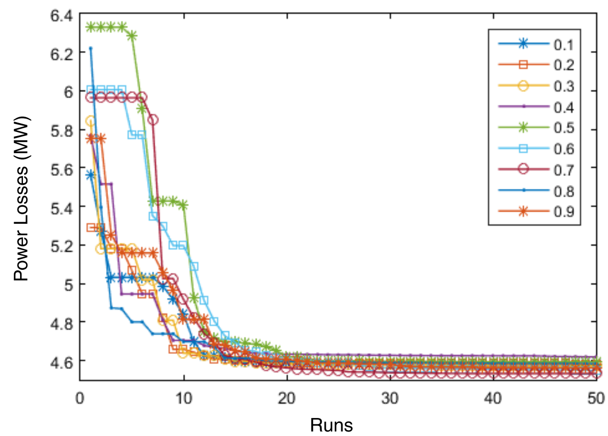

FIGURE 2. FPSOGSA-Entropy Convergence Curve for IEEE30 Standard (13 Variables) at different fractional orders for power losses minimization.

The consideration of worst case reported only in term of comparing every fractional order but its values is reported best as compared to the base case. Furthermore, the best alpha would be further run for the 100 autonomous trails which gives the lowermost minimum power line losses to 4.5323 MW at fractional alpha order $\alpha = 0.7$.

B. MINIMAZATION OF VOLTAGE DEVIATION TESTED ON IEEE 30 STANDARD (13 CONTROL VARIABLES)

The proposed FPSOGSA-Entropy algorithm is further run for the second scenario in order to find the lowest voltage

TABLE 4. Comparison of percentage of power losses minimization for IEEE30 standard (19 variables).

Compared Results	Base Case	GSA [35]	MFO [67]	PSOGSA [35]	SGA(Ff2) [71]	FA [69]	CKH [70]	PSO-TS [68]	FPSOGSA [72]	FPSOGSA-Entropy
Plosses, MW	5.811	4.5515	4.5128	4.5309	4.5399	4.7694	5.4285	4.5213	4.4121	4.3248
% of losses	-	21.67	22.34	22.03	21.87	17.92	6.58	22.19	24.07	25.57

TABLE 5. Optimal values of control variables for IEEE30 standard (19 variables) in case of minimization of losses.

Control Variable	GSA [35]	MFO [67]	PSOGSA [35]	SGA Ff2 [71]	FA [69]	CKH [70]	PSO-TS [68]	FPSOGSA [72]	FPSOGSA-Entropy
$V_{gt\,1}$	1.1000	1.1	1.1000	1.1000	1.1	1.0500	1.1000	1.0100	1.1000
$V_{gt\,2}$	1.0944	1.0943	1.0944	1.0940	1.0644	1.0473	1.0943	1.0066	1.0950
$V_{gt\,5}$	1.0748	1.0747	1.0749	1.0745	1.07455	1.0293	1.0749	0.9903	1.0773
$V_{gt\,8}$	1.0768	1.0766	1.0767	1.0767	1.0869	1.0350	1.0766	0.9883	1.0778
$V_{gt\,11}$	1.1000	1.1	1.1000	1.1000	1.09164	1.0500	1.1000	1.0100	1.0999
$V_{gt\,13}$	1.1000	1.1	1.1000	1.1000	1.099	1.0500	1.1000	1.0099	1.1000
$T_{c\,6\text{-}9}$	1.0399	1.0433	1.0452	1.0510	1	0.9916	0.9744	1.0285	1.0421
$T_{c\,6\text{-}10}$	0.9000	0.9	0.9000	0.9000	0.94	0.9538	1.0510	0.9030	0.9146
$T_{c\,4\text{-}12}$	0.9827	0.97912	0.9794	0.9830	1	0.9603	0.9000	0.9283	0.9887
$T_{c27\text{-}28}$	0.9699	0.96474	0.9651	0.9670	0.97	0.9670	0.9635	0.9182	0.9751
$Q_{c\,10}$	3.5717	5	5.0000	0.0500	3	0.0092	0.0500	29.9905	4.0574
$Q_{c\,12}$	3.0984	5	5.0000	0.0500	4	0.0000	0.0500	23.8555	3.8563
$Q_{c\,15}$	3.2925	0.048055	5.0000	0.0500	3.3	0.0153	0.0500	13.2088	1.7156
$Q_{c\,17}$	4.0166	5	5.0000	0.0500	3.5	0.0497	0.0500	14.3632	2.5888
$Q_{c\,20}$	3.0309	4.0263	3.9792	0.0435	3.9	0.0302	0.0386	0.2464	4.1546
$Q_{c\,21}$	4.0339	5	5.0000	0.0500	3.2	0.0500	0.0500	0.0683	4.9980
$Q_{c\,23}$	2.9946	2.5193	2.4583	0.0270	1.3	0.0134	0.0500	0.3625	4.6668
$Q_{c\,24}$	4.3499	5	5.0000	0.0500	3.5	0.0500	0.0500	8.3715	3.3289
$Q_{c\,29}$	2.6902	2.1925	2.1865	0.0240	1.42	0.0121	0.0213	0.1874	1.9032
$P_{losses,}$ MW	4.5515	4.5128	4.5309	4.5399	4.7694	5.4285	4.5213	4.4121	4.3248

deviation value. The proposed algorithm is run for 10 independent trails on different fractional alpha orders range between $\alpha = [0.1, \ldots, 0.9]$.

The Fig. 3 illustrates the performance of each alpha while the best and the worst outcomes are reported at $\alpha = 0.4$ gives 0.1031p.u and $\alpha = 0.3$ gives 0.1280p.u respectively. Furthermore, the best fractional order is run for 100 autonomous trails which gives the lowermost voltage deviation value reported as 0.0914 p.u.

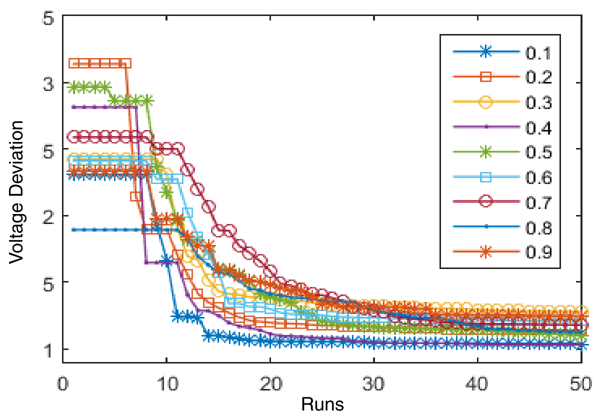

FIGURE 3. FPSOGSA-Entropy Convergence Curve for IEEE30 Standard (13 Variables) at different fractional orders for voltage deviation minimization.

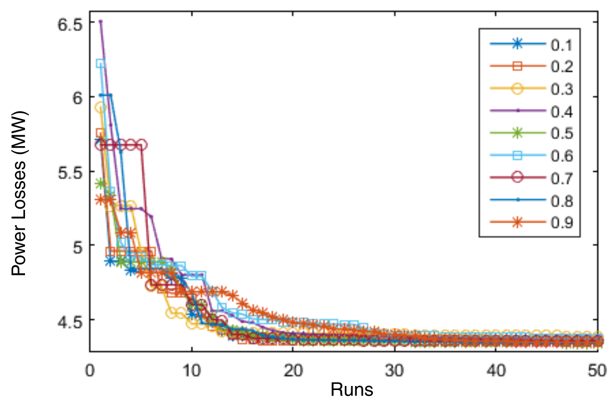

FIGURE 4. FPSOGSA-Entropy Convergence Curve for IEEE30 Standard (19 Variables) performed at different fractional alpha orders for power losses minimization.

In this scenario, the voltage deviation reported for FPSOGSA [72] is 0.1025p.u while the best performance achieved by FPSOGSA-Entropy is reported to 0.0914p.u.

C. MINIMAZATION OF POWER LINE LOSSES TESTED ON IEEE 30 STANDARD (19 CONTROL VARIABLES)

The consideration of the control variables for IEEE30 Standards in the third scenario is 19. It contains 41 branches, six generators (V_{gt}), four transformers tap settings (T_c) connect to the same buses and branches with the same range are given

TABLE 6. Optimal values of control variables for IEEE57 standard (25 variables) in case of minimization of power losses.

Control Variables	DE [36]	FODPSO [36]	GWO [14]	GSA [15]	CLPSO [71]	IWO [28]	FPSOGSA [72]	FPSOGSA-Entropy
$V_{gt\text{-}1}$	1.0600	1.04	1.0600	1.0600	1.0541	1.06	1.1000	1.1000
$V_{gt\text{-}2}$	1.0504	1.0298	1.0562	1.0582	1.0529	1.05912	1.0987	1.0981
$V_{gt\text{-}3}$	1.0440	1.0099	1.0370	1.0462	1.0337	1.04716	1.0871	1.0896
$V_{gt\text{-}6}$	1.0376	0.9776	1.0202	1.0391	1.0313	1.03817	1.0807	1.0864
$V_{gt\text{-}8}$	1.0550	0.9855	1.0449	1.0600	1.0496	1.05926	1.1000	1.1000
$V_{gt\text{-}9}$	1.0229	0.9676	1.0294	1.0432	1.0302	1.02729	1.0845	1.0821
$V_{gt\text{-}12}$	1.0323	0.9081	1.0319	1.0379	1.0342	1.0374	0.9600	1.0295
$T_{c\,4\text{-}18}$	0.9669	0.9	0.9847	0.9054	0.9900	1.05	1.0071	0.9842
$T_{c\,4\text{-}18}$	0.9902	0.9209	0.9326	0.9978	0.9800	1.0	1.0847	1.0483
$T_{c\,21\text{-}20}$	1.012	1.0268	0.9576	1.0021	0.9900	1.07	0.9959	0.9578
$T_{c\,24\text{-}26}$	1.0087	1.0075	0.9968	1.0180	1.0100	1.02	0.9908	0.9014
$T_{c\,7\text{-}29}$	0.9707	0.9070	0.9636	0.9712	0.9900	0.97	0.9964	0.9836
$T_{c\,34\text{-}32}$	0.9686	0.9871	0.9812	0.9692	0.9300	0.99	1.0072	0.9138
$T_{c\,11\text{-}41}$	0.9008	0.9010	1.0621	0.9683	0.9100	0.9	0.9900	0.9055
$T_{c\,15\text{-}45}$	0.9660	0.9	0.9755	0.9717	0.9700	0.96	0.9906	0.9106
$T_{c\,14\text{-}46}$	0.9507	0.9	0.9639	0.9530	0.9500	0.95	1.0028	0.9130
$T_{c\,10\text{-}51}$	0.9641	0.9165	0.9723	0.9691	0.9800	0.98	0.9900	0.9001
$T_{c\,13\text{-}49}$	0.9246	0.9	0.9248	0.9242	0.9500	0.93	1.0027	0.9389
$T_{c\,11\text{-}43}$	0.9502	0.9	0.9554	1.0387	0.9500	0.99	1.0844	1.0287
$T_{c\,40\text{-}56}$	0.9966	0.9980	1.1000	1.0497	1.000	1.01	1.0023	1.0485
$T_{c\,39\text{-}57}$	0.9628	0.9945	0.9976	1.0668	0.9600	1.04	0.9900	0.9001
$T_{c\,9\text{-}55}$	0.96	0.9	0.9845	0.9807	0.9700	0.96	1.0951	1.0498
Q_{c18}	0.09782	4	1.8917	0.1863	0.09880	0.0442	4.9846	5.0000
$Q_{c\,25}$	0.05899	15	5.2489	4.0488	0.0542	0.0433	4.9992	4.9978
$Q_{c\,53}$	0.06289	11.678	5.1513	4.8099	0.0628	0.0615	4.3653	4.9652
P_{losses} MW	24.54	26.680	24.7523	24.4922	24.89	24.5939	22.9185	21.7753

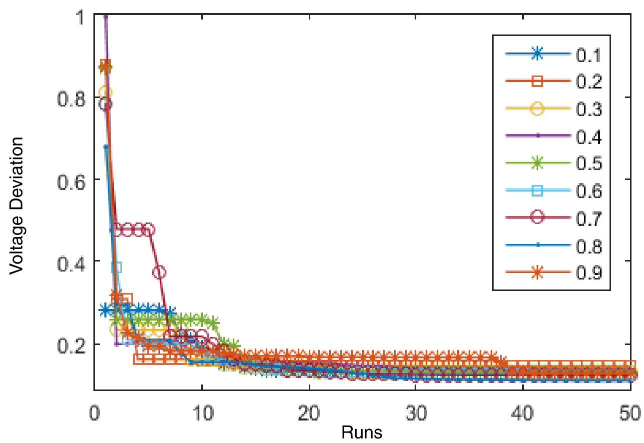

FIGURE 5. FPSOGSA-Entropy Convergence Curve for IEEE30 Standard (19 Variables) performed at different fractional alpha orders for voltage deviation minimization.

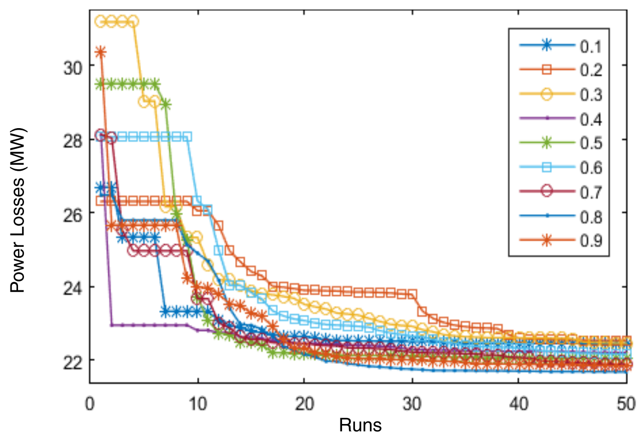

FIGURE 6. FPSOGSA-Entropy Convergence Curve for IEEE57 Standard (25 Variables) performed at different fractional alpha orders for power line losses minimization.

in scenario 1. While, the shunt reactive compensators (Q_c) are connected to the buses 10, 12,15,17,20,21,23,24 and 29 with the range between [0-30MVAr] respectively. The real and reactive load demands for this scenario are the same as given in the previous scenario.

The results are compared with the different algorithms are given in Table 5 while the outcomes attain from the proposed FPSOGSA-Entropy algorithm is leading at 4.3248 MW in case of minimization of power line losses. The reduction in power line losses % are given in Table 4, the base case values

TABLE 7. Comparison of percentage of power losses minimization for IEEE57 standard (25 variables).

Compared Results	Base Case	DE [36]	FODPSO [36]	GWO [14]	GSA [15]	CLPSO [71]	IWO [28]	FPSOGSA [72]	FPSOGSA-Entropy
Plosses, MW	27.86	24.54	26.680	24.7523	24.4922	24.89	24.5939	22.9185	21.7753
% of losses	-	11.92%	4.23%	11.22	12.08	10.66	11.72	17.76	21.84

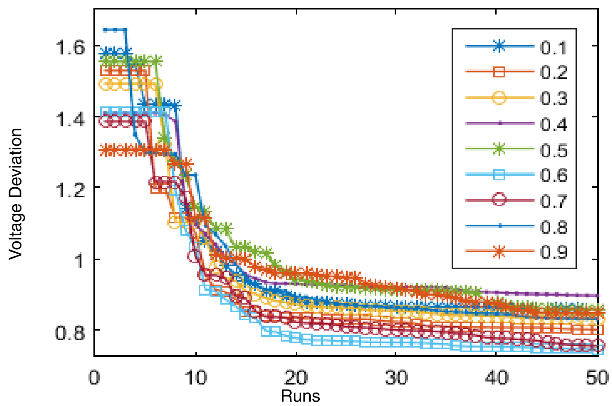

FIGURE 7. FPSOGSA-Entropy Convergence Curve for IEEE57 Standard (25 Variables) performed at different fractional alpha orders for voltage deviation minimization.

is considering here 5.811 MW for comparing the results from different algorithms.

The power line losses reduction % in MW are given such as; GSA is 21.67%, MFO is 22.34%, SGA(Ff1) is 21.37%, PSOGSA is 22.03%, FA is 17.92%, CKH is 6.58%, PSO-TS is 22.19%, FPSOGSA is 24.07% while FPSOGSA-Entropy is reported as 25.57% respectively. The Fig. 4, illustrates the convergence performance curve of the FPSOGSA-Entropy algorithm at the different fractional alpha order range $\alpha = [0.1, \ldots, 0.9]$ in order to attain the best alpha.

In this scenario, the best alpha is report at fractional order $\alpha.5$ with minimum losses to 4.3410 MW while the worst results reported at $\alpha = 0.3$ with minimum power losses 4.3849 MW respectively.

The best fractional order alpha $\alpha.5$ is further used to run the proposed algorithm for 100 autonomous trails to get minimization in power losses which is reported at 4.3248 MW.

D. MINIMAZATION OF VOLTAGE DEVIATION TESTED ON IEEE 30 STANDARD (19 CONTROL VARIABLES)

The proposed FPSOGSA-Entropy algorithm is further run for the fourth scenario to find the minimum voltage deviation (*VD*). The proposes FPSOGSA-Entropy algorithm is run for

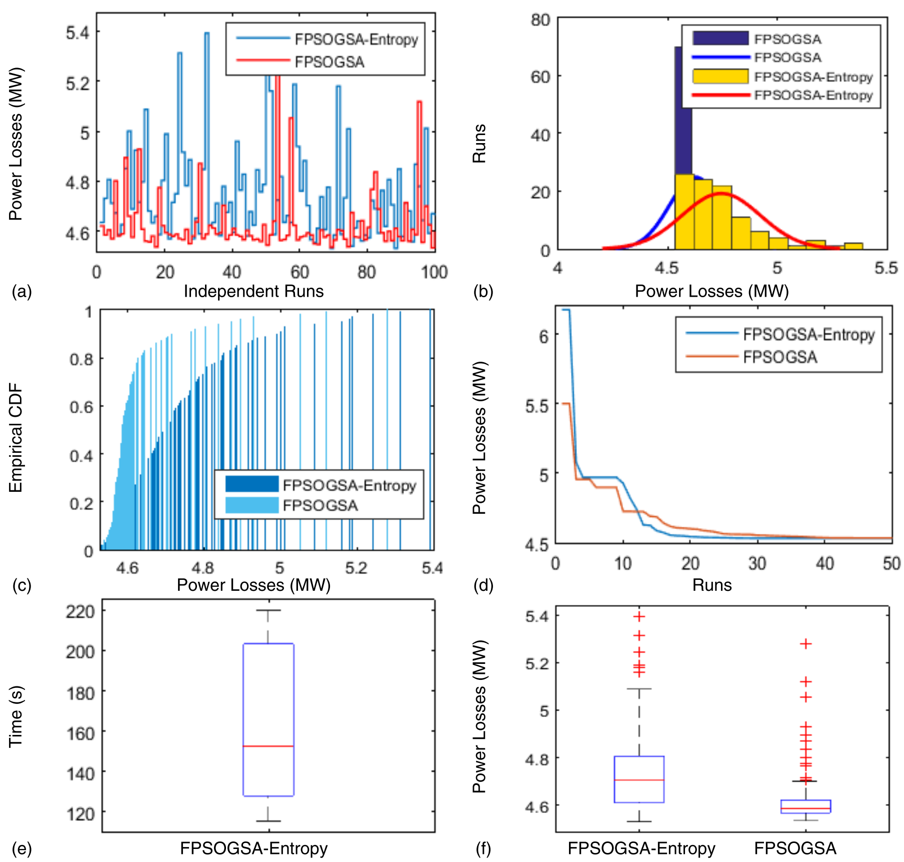

FIGURE 8. FPSOGSA-Entropy and FPSOGSA statistical analysis results for IEEE 30 Standard (13 Variables) for Power Losses. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.

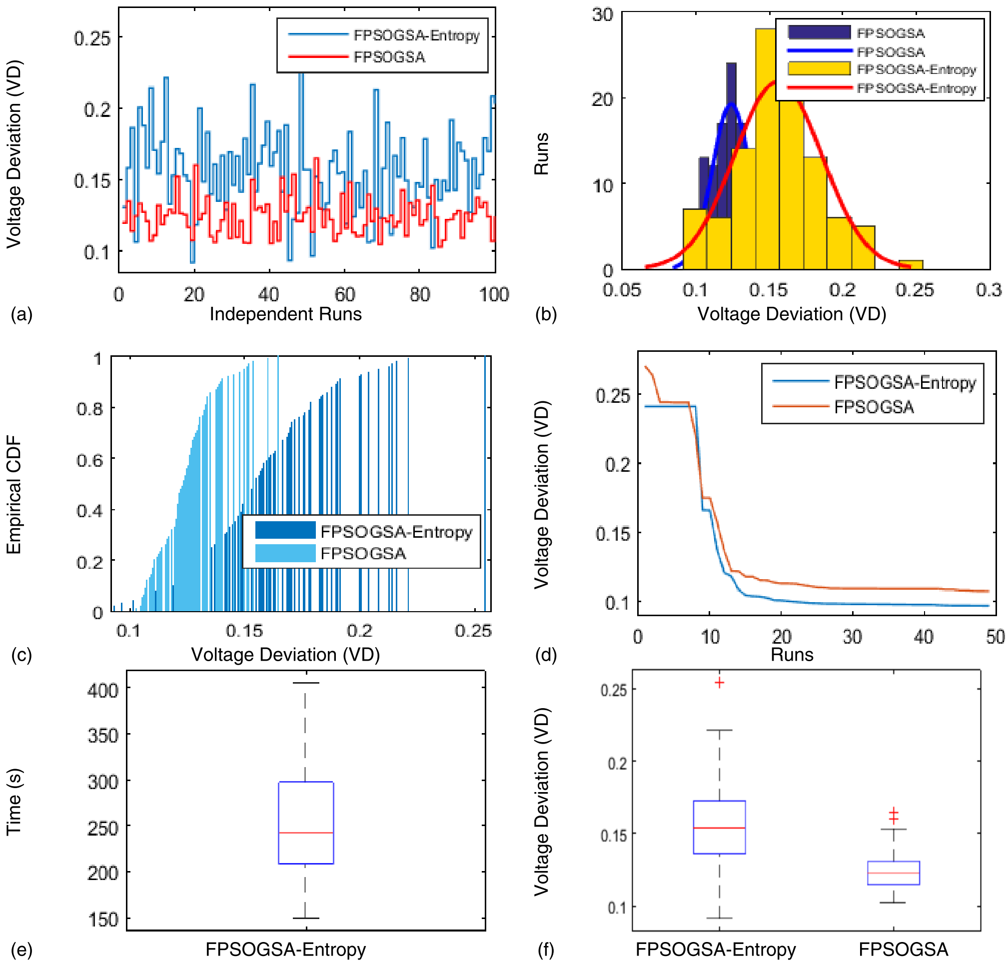

FIGURE 9. **FPSOGSA-Entropy and FPSOGSA statistical analysis for IEEE 30 Standard (13 Variables) for Voltage Deviation. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.**

10 autonomous trails for each fractional alpha orders range between $\alpha = [0.1, \ldots, 0.9]$.

The Fig. 5 illustrates the performance of each alpha while the best and the worst outcomes are reported at $\alpha = 0.8$ gives 0.1243p.u and $\alpha = 0.2$ gives 0.1473p.u respectively. Furthermore, the best fractional order $\alpha = 0.8$ for this scenario is run for 100 autonomous trails which gives the lowermost value of voltage deviation which is reported as 0.1168 p.u.

The voltage deviation in this scenario, FPSOGSA algorithm [72] is reported to 0.1468p.u while the FPSOGSA-Entropy is reported to 0.1243p.u. Hence, the performance of FPSOGSA-Entropy for voltage deviation is superior to FPSOGSA algorithm.

E. MINIMAZATION OF POWER LINE LOSSES TESTED ON IEEE 57 STANDARD (25 CONTROL VARIABLES)

In order to consider the performance and the effectiveness of the proposed FPSOGSA-Entropy algorithm in a large-scale power system, IEEE 57 bus standards is introduced as the test system in this scenario with 25 variables. The test system contains seven generators (V_{gt}) at the buses 1, 2, 3, 6, 8, 9 and 12 with the range between $\alpha = [0.95 - 1.1]$. There will be 15 branches of transformer tap settings (T_c) range [0.9-1.1], while three shunt compensators are connected to buses 18,25 and 53 range $[-30,30]$ respectively.

The optimal values of the control variables settings for the different algorithms are given in Table 6. The results revealed the better performance of the proposed FPSOGSA-Entropy with minimum power line losses reported at 21.7753 MW.

The reduction in power line losses % are given in Table 7 while the base case values is considering here is 27.86 MW for comparing the results from different techniques. The power losses % in MW are given such as; DE is 11.92%, FODPSO is 4.23%, GWO is 11.22%, GSA is 12.08%, CLPSO is 10.66%, IWO is 11.72, FPSOGSA is 17.76% while the proposed FPOSGSA-Entropy is recorded as 21.84% respectively. The Fig. 6 illustrates the performance proposed algorithm at the different fractional alpha order range $\alpha = [0.1, \ldots, 0.9]$ in order to get the best alpha. The best alpha is report at fractional order $\alpha .8$ with minimum power line

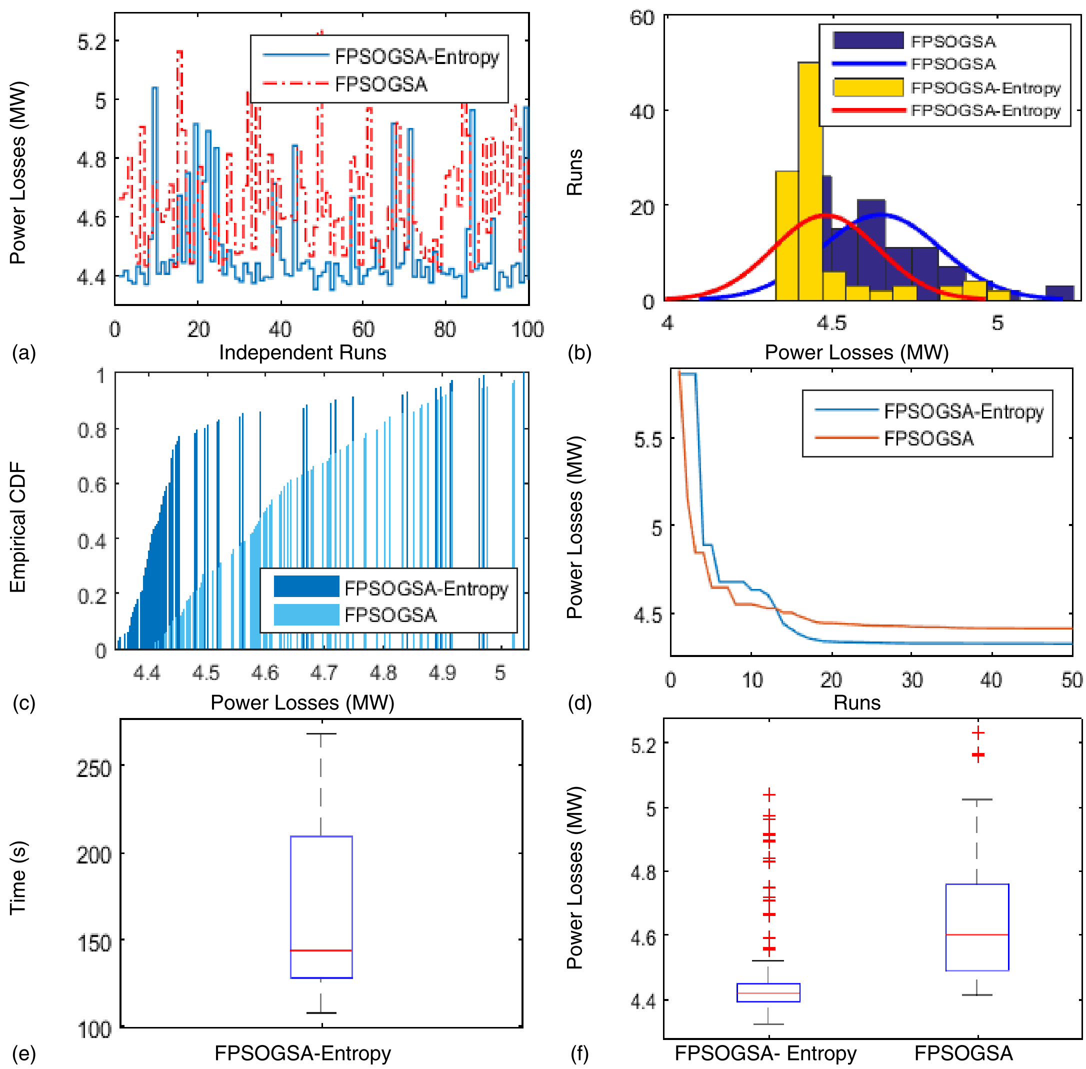

FIGURE 10. **FPSOGSA-Entropy and FPSOGSA Statistical Analysis for IEEE 30 Standard (19 Var) for Power Losses. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.**

losses to 21.8826 MW while the worst results reported at $\alpha = 0.2$ with 22.5425 MW respectively. The best fractional order alpha α.8 is further used to run the proposed algorithm for 100 independent trails to get minimization in power line losses which is reported at 21.7753 MW.

F. MINIMAZATION OF VOLTAGE DEVIATION TESTED ON IEEE 57 STANDARD (25 CONTROL VARIABLES)

The proposed FPSOGSA-Entropy algorithm is run for the sixth scenario to find the second objective while using IEEE 57 Standard to minimize the voltage deviation (*VD*). range between $\alpha = [0.1, \ldots, 0.9]$ to attain the minimum voltage deviation at best alpha.

The Fig. 7 illustrates the performance of each alpha while the best and the worst outcomes are reported at $\alpha = 0.6$ gives 0.7468p.u and $\alpha = 0.1$ gives 0.8590p.u respectively.

Furthermore, the best fractional order $\alpha = 0.6$ for this scenario is run for 100 autonomous trails which gives the lowermost value of voltage deviation which is reported as 0.7378 p.u. The voltage deviation in case of FPSOGSA algorithm [72] is reported to 0.8017.u while the voltage deviation achieved by FPSOGSA-Entropy is 0.7378p.u that endorse the effectiveness of FPSOGSA-Entropy over FPSOGSA.

V. STATISTICAL ANALYSIS OF FPSOGSA-ENTROPY WITH FPSOGSA ALGORITHM

In this approach, the performance of FPSOGSA-Entropy is further measured by taking the comparatively analysis with FPSOGSA algorithm through statistical analysis for all given scenarios considering at the best alpha orders. For this purpose, the hundred autonomous tails are performed to illustrate the authentic inferences between the performance of FPSOGSA-Entropy and FPSOGSA. The statistical analysis is performed by using both algorithms for optimal reactive power dispatch problem on the basis of minimum fitness in

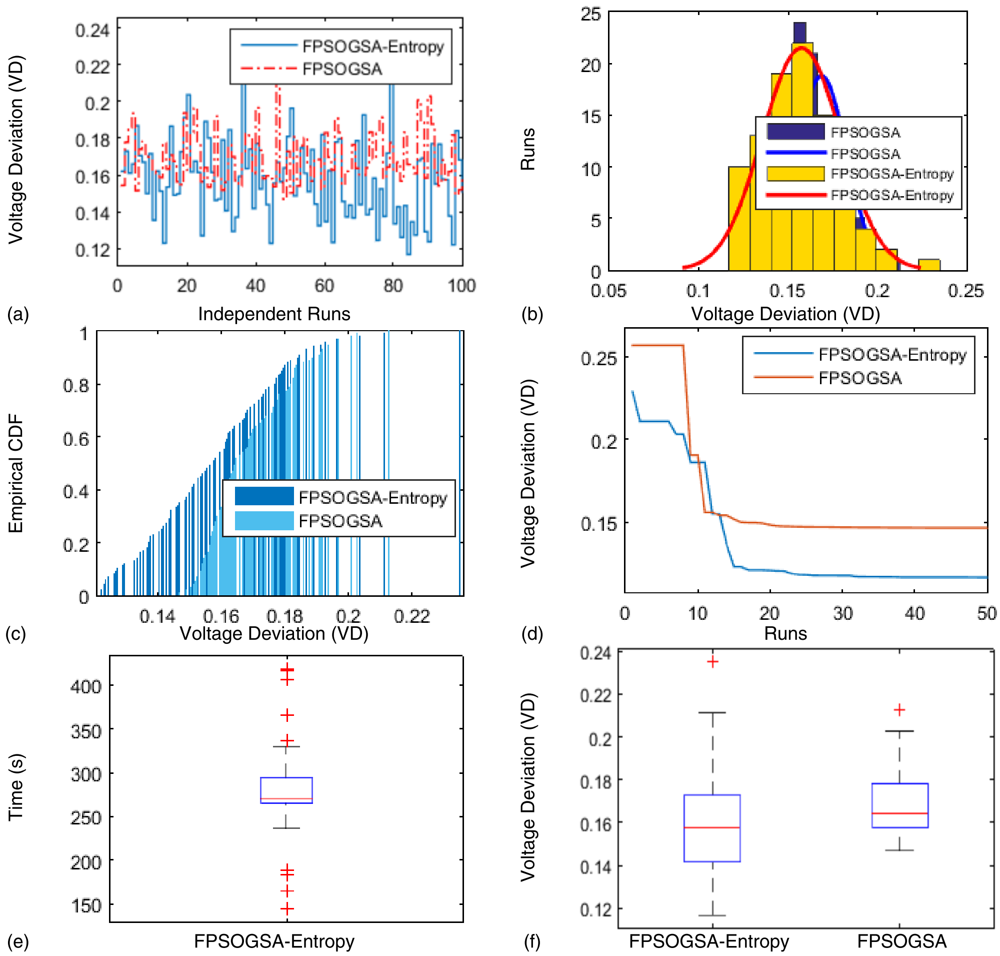

FIGURE 11. FPSOGSA-Entropy and FPSOGSA Statistical Analysis for IEEE 30 Standard (19 Variables) for Voltage Deviation. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.

every autonomous simulation, boxplot, empirical CDF, minimization plots in case of each scenarios, histogram curves and time complexity analysis.

The outcomes are given in sub-Figs. 8(a)-13(a) depicts the minor variations observed in all cases of minimum power line losses and voltage deviation which determines the best precision of FPSOGSA-Entropy over FPSOGSA for entire autonomous trails. The histogram outcomes are demonstrated in sub-Figs. 8(b)-13(b), most of the autonomous simulations of FPSOGSA-Entropy provides the tiniest gauges of the precision over FPSOGSA. The empirical CDF in sub-Figs. 8(c)-13(c) indicates towards the outcomes attained during performed all autonomous simulations for both algorithms. The fitness values are recorded less than the base case which demonstrate the best an iterative process attained from FPSOGSA-Entropy. The sub-Figs. 8(d)-13(d) illustrates the comparison of the minimum fitness in case of power line losses and voltage deviation attained by FPSOGSA-Entropy and FPSOGSA algorithms for IEEE30 (13,19 variables) and IEEE57 (25 variables). While, the best fitness minimization is achieved by FPSOGSA-Entropy algorithm for all given scenarios. The sub-Figs. 8(e)-13(e) demonstrated the execution time of FPSOGSA-Entropy to ORPD problem for two given objectives functions; power line losses and voltage deviation. The detail of comparison of execution time of between FPSOGSA-Entropy and FPSOGSA algorithm is given in Table 9 and the data spreading is very close in each quartile during the independent trials.

The computational efficiency in terms of time complexity of the proposed method for different scales test systems is now conducted and compared with other state of the art counter parts designed to solve ORPD problems. A comparison between the computational time complexity of the proposed optimization framework i.e., FPSOGSA-Entropy evolution, with other optimizers including the fractional order Darwinian PSO (FO-DPSO) [36], simple genetic algorithm (SGA) [80], multi agent PSO (MAPSO) [79], evolutionary programming EP [3] and seeker optimization algorithm (SOA) [18] is tabulated in Table 8 along with adopted

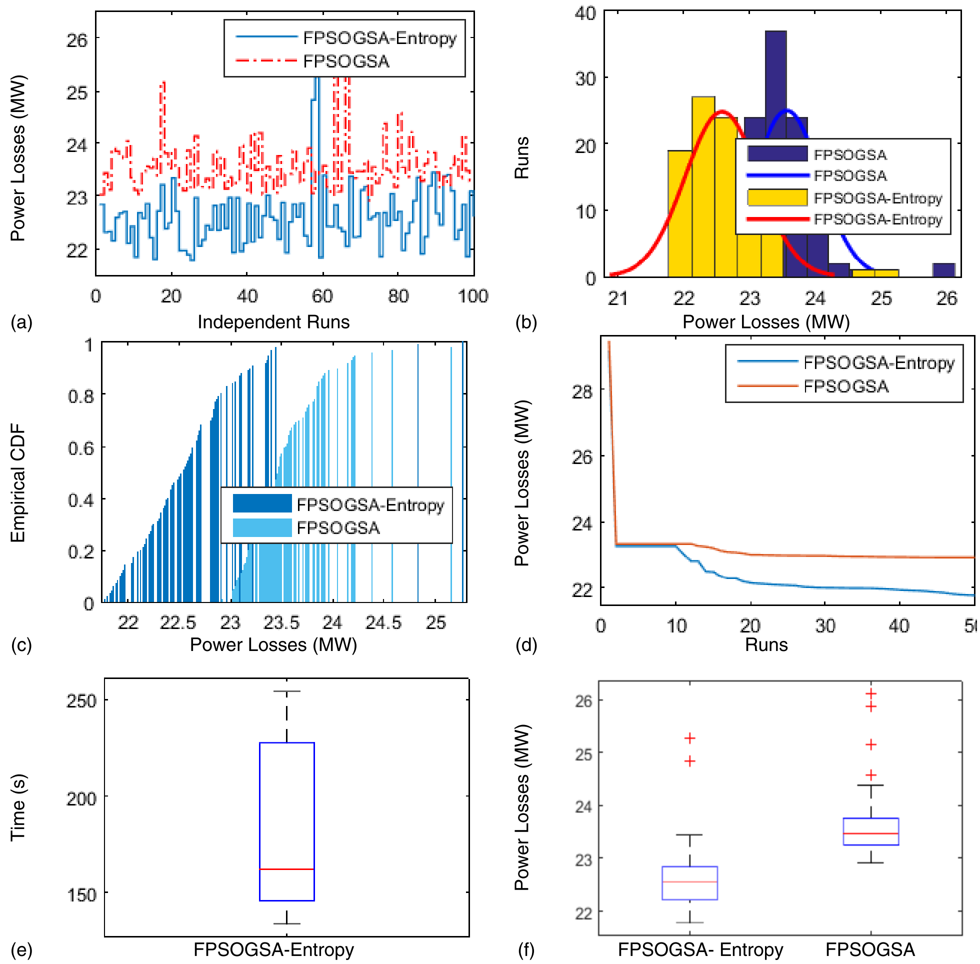

FIGURE 12. FPSOGSA-Entropy and FPOGSA Statistical Analysis for IEEE 57 Standard (25 Variables) for Power Losses. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.

TABLE 8. Computational efficiency of the proposed method compared to different scale systems.

S.no	Reference	Specification	Bus	Time (s)
1.	FODPSO Run = 100	MATLAB 2015, Core i7 CPU 3.40, 8 GB RAM	30 57	42 55
2.	MAPSO Run = 50	MATLAB 6.5, Pentium 4, CPU – NA, RAM- NA	30	41.93
3.	SOA Run = 30	MATLAB 7, Pentium 4, CPU 2.4, 512 MB RAM,	57 118	391.23 -n/a
4.	SGA Run=50	MATLAB 6.5, Pentium 4, CPU – NA, RAM- NA	30	156.34
5.	EP	MATLAB 6.5, Pentium 4 128 MB RAM, CPU-NA	14 30	72-78 103-118

system (machine) specifications and number of autonomous simulations.

One may observe that there is no considerable difference in execution time during each run of the FPSOGSA-Entropy evolution and other counterparts' techniques. Although, the computational efficiency of the proposed algorithm is at the higher side due to its inherent long memory that keeps the track of particle's trajectory, this limitation is overwhelmed by its fast convergence rate which is evident from the learning behaviors as depicted in Figs 8(e)-12(e). In addition, the computational efficiency investigation in such manner is very difficult to conclude and justify because evaluated outcomes are machine dependent which may have diverse hardware specification, i.e., cloud, CPU, RAM etc., operating mechanisms, i.e., evolutionary computing, swarm intelligence etc., on software environment, i.e., MATHEMATICA, MATLAB, operating systems etc., initial parameters i.e., generations, flights, population and swarm size etc.

The boxplots are given in sub-Figs. 8(f)-13(f) illustrates the stretching of data values and the outliers that are closed to the median. It disclosed the accurate optimization process attained by FPSOGSA-Entropy over FPSOGSA. The overall statistical results discussed in this section are proved the robustness, consistency and the stability of the proposed FPSOGSA-Entropy over FPSOGSA algorithm. The entropy evaluation technique implemented in FPSOGSA indicates towards the excellence performance of the novel FPSOGSA-Entropy algorithm.

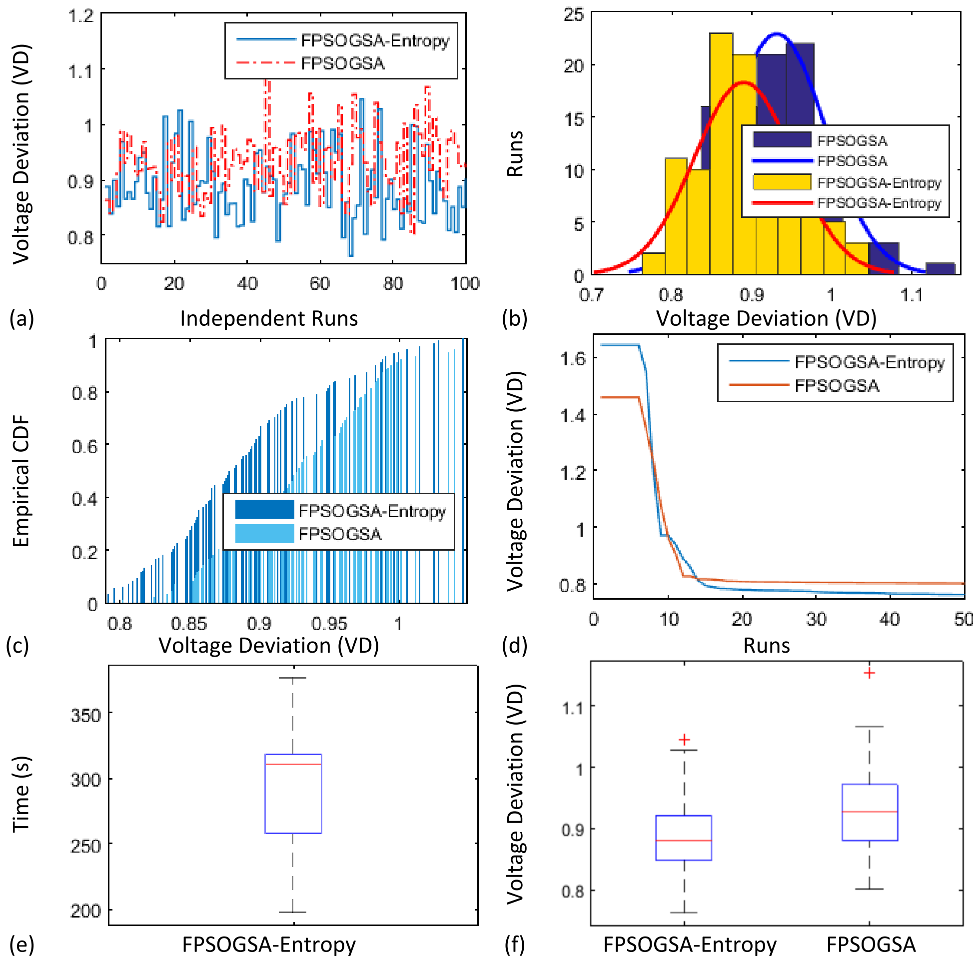

FIGURE 13. FPSOGSA-Entropy and FPSOGSA Statistical Analysis for IEEE 57 Standard (25 Variables) for Voltage Deviation. (a) Stairs (b) Histogram (c) ecdf Plot (d) Minimization of Power losses (e) Boxplot-Time complexity of FPSOGSA-Entropy (f) Box plot Gauge.

TABLE 9. Comparison of execution time (s) of FPSOGSA and FPSOGSA-Entropy for ORPD problems.

	FPSOGSA [72]			FPSOGSA-Entropy		
	IEEE30 (13 Var)	IEEE30 (19 Var)	IEEE57 (25 Var)	IEEE30 (13 Var)	IEEE30 (19 Var)	IEEE57 (25 Var)
Ploss	153.3392	145.0689s	195.0752s	160.55385	164.0057s	180.9937s
VD	189.1632s	200.3447s	247.3561s	254.1831	281.2666	296.7321s

VI. CONCLUSION

A novel hybrid optimization FPSOGSA with entropy evolution technique is proposed and successfully applied on IEEE 30 and 57 Bus Standards to solve two objective functions of optimal reactive power dispatch such as; minimization of power line losses and voltage deviation. The concept of fractional derivative implemented with Shannon entropy to improve the performance of hybrid PSOGSA algorithm with enhancing the abilities like memory effects, velocity and updating positions with convergence rate to find the global best solution. The outcomes of FPSOGSA-Entropy are further compared to different algorithms such as HSA, DE, R-DE, MFO, GWO, FODPSO-EE, PSOGSA, SGA(Ff2), FA, CKH, PSO-TS, CLPSO, IWO and FPSOGSA that depicted the best outcomes and performance achieved by the proposed FPSOGSA-Entropy algorithm in case of each given scenarios.

It is recommended that the both entropy and fractional techniques will be implemented to design the new evolutionary and fractional swarming algorithms to solve the problems related to engineering and power sectors [73]–[78] in future.

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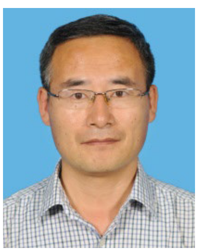

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