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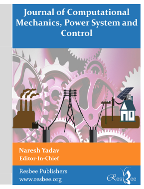

Hybrid Particle Swarm Optimization and Firefly Algorithm for Distributed Generators Placements in Radial Distribution System

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Abstract: In this work, a novel application of hybrid Particle Swarm Optimization (PSO) and Firefly (FF) method is proposed with an intend of determining the optimal positioning and sizing of Distributed Generators for multi-objectives. Here, the multi-objectives like minimization of loss of power, enhancement of voltage profile, and minimization of operation cost fed to inequality and equality constraints. Moreover, the developed technique is shown on IEEE 33-bus and 69-bus RDS. Here, every test system is contemplated for two diverse cases: case 1: positioning Type 1 DGs (only real power injection). Case 2: positioning Type 2 DGs (both real and reactive power injection). Finally, the experimentation outcomes attained from the developed method are evaluated with other renowned optimization methods; and the proposed method shows more efficient for multi-objectives.

Keywords: Power System; Distributed Generation; Multi-Objectives; Bus System; Optimization Algorithms

Nomenclature

Abbreviations	Descriptions
DG	Distributed generation
NO	Normally Open
DS	Distribution Systems
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimizer
OPAS	Optimal Placement and Sizing
DN	Distribution Network
NLPCI	Nonlinear Load Position based APF Current Injection
HLFs	Harmonic Load Flow
AA	Affine Arithmetic
PV	Photovoltaic
IHP	Iterative Harmonic Penetration
CVD	Cumulative voltage deviation
IRRO	Improved Raven Roosting Optimization
CAT	Combined Analytical Technique
GA	Genetic Algorithm
NC	Normally Closed
RDS	Radial Distribution System
APF	Active Power Filter
PEM	Point-Estimate Method
LGSA	Legendre Series Approximation
VSI	Voltage Stability Index
RDN	Radial Distribution Network
DGs	Distributed Generation
VDI	Voltage Deviation Index
LU	Lower and Upper

1. Introduction

Electrical power demand is progressively growing. Whereas fulfilling the power demand has to turn out to be the most important apprehension in minimization of network power loss. DG plays a significant role to provide electrical power and to minimize losses of the network. DG is described as a medium or small electrical power generating system deployed earlier to load. DGs might be a nonconventional else conventional energy source. The instance of DGs is microturbine, wind turbine, solar cell, diesel generator fuel cell, and so on [1] [3].

In general, DG units are linked at distribution with the intention that, transmission and distribution loss can be minimized. A large amount of the DS is radial that is usually provided at one point that is power flow, and sub-station in RDS, which is unidirectional without DG. It comprises of few NO and NC switches. The most important causes for high distribution loss are minimum voltage levels and extensive distribution load area [3].

In the DN, the appropriate positioning of DG is very important and a demanding task. If DGs are not correctly positioned in DN, it might cause a rise in electric power losses rather than minimizing the similar. Consequently, the DG positioning at an appropriate strategic position is a significant task. Simultaneously, to minimize the network losses optimum sizing of DG plays a vital role. Accordingly, to determine the optimum position and attaining the suitable sizing of DG have to turn out to be a motivating topic to the research community [4].

There are numerous approaches obtainable to reduce the losses, namely DG positioning, network reconfiguration, capacitor positioning, load management, etc. DG technology attracts additional concentration owing to the global concerned regarding the energy predicament and progression in technology [13]. Also, there are several techniques developed for the positioning and sizing of DG units [9] [10] [11] [12]. Many approaches are based on artificial intelligence and heuristic approaches. An approach based on the analytical method to enhance the voltage profile and to minimize the power loss in arbitrarily distributed load circumstances using minimum power factor for single DG and multi DG systems. Also, an enhanced analytical approach for recognition of the optimal power factor and the optimal position for positioning multiple DGs to attain loss minimization in large-scale main DN is proposed. A GA and discrete PSO based technique for optimal planning of DG in DN to reduce loss and enhance consistency also presented. In the DS a technique for optimal siting and sizing of DGs at any bus to reduce losses and establish that the total losses in the DN would minimize by almost 85% if DGs were positioned at the optimal positions through optimal sizes is developed. A multi-objective performance index-based approach exploiting GA for optimal sizing and the positioning of DG resources in DS was explained.

The most important objective of this article is to propose a novel hybrid meta-heuristic optimization approach that is PSO and Firefly algorithm. Moreover, the developed technique is examined on 33 bus and 69 bus test systems by considering multi-objective for diverse cases. The results attained using the proposed approach is evaluated with that of other renowned methods and it shows that the proposed method is very efficient.

2. Literature Review

In 2020, Srinivas Nagaballi and Vijay S. Kale [1], developed a weighted multi-objective index represents an extensive range of technical problems like reactive and active system power losses, line loading, voltage profile, and voltage stability, these were implicit as technical enhancements effects in Radial Distribution System. A new optimization technique named as an IRRO approach, which was implemented for optimal deployment of Distributed Generation in the Radial Distribution System.

In 2019, Vinod Raj and Boddeti Kalyan Kumar [2], introduced a novel elaboration for complex affine multiplication of affine arithmetic based distribution power flow study that does not attempt to produce some additional noise phrase for the ensuing complex affine product. The developed enhanced affine arithmetic based distribution power flow analysis was examined on IEEE 33, 69, 202, and 874 bus RDS.

In 2019, Ashokkumar Lakum and Vasundhara Mahajan [3], discussed the effect of DG penetration on the OPAS of APF. Also, the novel NLPCI approach was developed to place the possible buses for the position of APF in attendance of nonlinear load merely and in attendance of DG. Here, the GWO was exploited to identify APF optimal size.

In 2020, F.J. Ruiz-Rodriguez et al [4], presented a novel CAT for iterative HLFs in attendance of correlated input uncertainties from Photo Voltaic systems in Radial Distribution Systems. This method integrates PEM, a probabilistic elaboration, and complex AA, an interval formulation. Different techniques were considered, this CAT include IHP that presents a method to contract using communication of setting the harmonic voltage on PV harmonic current.

In 2017, Ting-Yen Hsieh et al [5], developed a new Z-bus matrix-building method based on graph theory as a choice technique for RDS. The developed method was based on the branch-path occurrence matrix K of an RDN as contrasting to a conventional Z-bus building method and inverse Y-bus matrix about the LU triangular matrix technique. The benefits of the developed method comprise minimum execution time, less logical judgments, and appropriateness for computing-assisted analyses. In all power systems the method obsessed possible for application analyses associated with a Z-bus impedance matrix.

In 2019, Rui Wang et al [6], developed a novel electric load forecasting system by the integration of data preprocessing. Moreover, hybrid optimization techniques, and several single classical forecasting techniques that successfully overwhelm the defects of single conventional forecasting techniques and obtain higher forecasting accurateness than that of single technique optimization.

3. Objective Function

The most important objective of the developed technique is to decide optimal positioning and sizing of Distributed Generators which reduces multi-objective function fed to several constraints in the DS.

3.1 Calculation of Power Flow

In DN, to turn up at the formulations to compute power flow, where r represents sending end node and $r+1$ represents receiving end node. Real and reactive power flows are computed exploiting a subsequent set of formulations, such as eq. (1) and (2), where R_r and S_r represents the real and reactive power flow from r, $R_{L(r+1)}$ and $S_{L(r+1)}$ indicates the real and reactive power load connected at $r+1$, $P_{r.r+1}$ and $Y_{r.r+1}$ represents the reactance connected between r and $r+1$, V_{r+1} indicates the voltage at the bus $r+1$, V_{min} and V_{max} indicates the value of the minimum and maximum bus voltage, K_i, K_r, K_S indicates the cost coefficient, $R_{toatl\ loss}$ indicates total power loss in the system.

$$R_{r+1} = R_r - R_{L(r+1)} - P_{r.r+1} * \frac{\left(R_r^2 + S_r^2\right)}{|V_r|^2} \tag{1}$$

$$S_{r+1} = S_r - S_{L(r+1)} - Y_{r.r+1} * \frac{\left(R_r^2 + S_r^2\right)}{|V_r|^2} \tag{2}$$

In the line, real power loss can be calculated exploiting eq. (3), and line voltages are computed exploiting Eq. (4)

$$R_{loss(r,r+1)} = P_{r,r+1} * \frac{\left(R_r^2 + S_r^2\right)}{|V_r|^2} \tag{3}$$

$$|V_{r+1}|^2 = |V_r|^2 - 2\left(P_{r,r+1} \cdot R_r + Y_{r.r+1} \cdot S_r\right) + \left(P_{r,r+1}^2 + Y_{r,r+1}^2\right) * \frac{\left(R_r^2 + S_r^2\right)}{|V_r|^2} \tag{4}$$

In the system, total power loss is computed by summing up all line losses as exhibited in Eq. (5)

$$R_{toatl\ loss} = \sum_{r=1}^{n-1} R_{loss(r,r+1)} \tag{5}$$

In the line power loss using DG is stated as eq. (6).

$$R_{DG,loss(r,r+1)} = P_{r,r+1} * \frac{\left(R_r^2 + S_r^2\right)}{|V_r|^2} \tag{6}$$

3.2 Minimization of Power loss

In the network, on one occasion the DG is positioned optimally, the total power loss will come down, total power loss ratio with DG to total power loss without DG is stated as power loss index and it is stated in eq. (7).

$$F_l = \min \frac{R_{totalloss}(\text{withDG})}{R_{totalloss}(\text{without DG})} \tag{7}$$

3.3 CVD Index.

VDI is stated in eq. (8),

$$F_2 = \min \frac{CVD(withDG)}{CVD(without\ DG)} \tag{8}$$

In eq. (9),

$$CVD = \begin{cases} 0 & 0.95 \le V \le 1.05_i \\ |1 - V_1| & else \end{cases} \tag{9}$$

3.4 Minimization of Operational Cost

The main objectives are to reduce operating costs. Cost formulation has 3 modules: the first module is the cost of real power supplied from the substation and the other 2 are the cost of real and reactive powers complete from DGs. Substation real power cost can be minimized by reducing the loss of power in the system and power cost supplied by DGs can be minimized by drawing minimum power from it, consequently, total operating cost can be minimized by exploiting the equation stated in eq. (10)

$$F_3 = \min \frac{TOC(withDG)}{TOC(without\ DG)} \tag{10}$$

In eq. (10)

$$TOC = K_i R_{loss} + \sum K_r R_{DG} + + \sum K_S S_{DG} \tag{11}$$

3.5 VSI

This is to choose the weakest bus which possesses more possibility to voltage collapse as well it is stated in eq. (12).

$$F_4 = \min \left[\frac{1}{SI(n)} \right] \tag{12}$$

3.6 Fitness Functions

The most important objective is to reduce multi-objectives namely minimization of power loss, enhancement of voltage profile, minimization of operating cost. The mathematical formulation of the objective model is stated in eq. (13).

$$O_f = \min(\beta_1 F_1 + \beta_2 F_2 + + \beta_3 F_3 + + \beta_4 F_4) \tag{13}$$

In eq. (14), β indicates the weighting factor,

$$\sum_{i=1}^{4} \beta_i = 1 \Lambda \beta_i \varepsilon [0,1] \tag{14}$$

As explained by below constraints

(a) Power Balance Formulation

$$\begin{aligned} R_{substitution} + \sum R_{DG} &= R_{load} + \sum R_{loss} \\ S_{substitution} + \sum S_{DG} &= S_{load} + \sum S_{loss} \end{aligned} \tag{15}$$

(b) DG Sizing Limits

$$\begin{aligned} R_{DG(min)} \le R_{DG(i)} \le R_{DG(max)} \\ S_{DG(min)} \le S_{DG(i)} \le S_{DG(max)} \end{aligned} \tag{16}$$

(c) Bus Voltage Limits

$$|V_{min}| \le |V_i| \le |V_{max}| \tag{17}$$

4. Proposed Hybrid PSO-FF Algorithm

The most important aim of the developed hybrid PSO-FF method is used to achieve a consistent accomplishment in estimating a restricted number of functions. In PSO balance among exploitation and exploration can be competently controlled exploiting control parameters of PSO [13] such as acceleration coefficients (c_1, c_2), (c_1, c_2) are arbitrary numbers in the range [0,1], and inertia weight (w). According to Eq. (18) the velocity of a particle (u) can be computed by the exploitation of these control parameters.

$$u_i(t+1) = wu_i(t) + c_1 r_1 (p_{best_i}(t) - Y_i(t)) + c_2 r_2 (g_{best_i}(t) - Y_i(t)) \tag{18}$$

$$Y_i(t+1) = Y_i(t) + U_i(t+1) \tag{19}$$

Hence, velocities are exploited to calculate the subsequent particles' new locations. Here, an optimization approach that integrates search capability of FF and PSO approaches was developed. A balance among exploitation and exploration is aspired to set up and it advantages the strengths of both approaches by using this integration. FF [12] has no velocity (u) and personal optimal location (p_{best}) memories in contrast with the particles. In developed hybrid integration of 2 approaches, generally, PSO is exploited in global search, as it presents fast convergence in exploration. Also, FF is exploited in local search, as it offers fine-tuning in exploitation. With dynamism altered inertia weight examines which regard as enhancements on preceding individual optimal, encompass accomplish something. The flowchart of the proposed hybrid PSO-FF is exhibited in Fig 1. Initially, input parameters which are exploited by both approaches in subsequent steps are introduced. Subsequently, in pre-defined search and velocity ranges, uniform particle vectors are arbitrarily prepared. Personal best (p_{best}) particles and Global (g_{best}) are computed and allocated. According to Eq. (21), in the subsequent evaluating phase, it is evaluated that if a particle has an enhancement in its fitness value in the final iteration. Subsequently, the present location is stored in a temporary variable (Y_{i-temp}) and new velocity and position are computed based on the Eq. (22) and Eq. (23).

$$w = w_i - \left(\left(w_i - w_f\right) / \text{iteration}_{max}\right) \times \text{iteration} \tag{20}$$

$$f(i,t) = \begin{cases} \text{true, if fitness}\left(\text{particle}_i^t\right) \leq g_{best}^{\,t-1} \\ \text{false, if fitness}\left(\text{particle}_i^t\right) > g_{best}^{\,t-1} \end{cases} \tag{21}$$

$$Y_i(t+1) = Y_i(t) + A_0 e^{-\gamma r_{ij}^2}\left(Y_i(t) - g_{best_i}^{\,t-1}\right) + a \in_i \tag{23}$$

$$U_i(t+1) = Y_i(t+1) - Y_{i-temp} \tag{24}$$

Hence, if a particle encompasses a superior or equivalent fitness value than preceding global optimal, it is understood that local search starts and the particle is touched by a derivative FF, or else particle will be handled by PSO and it continues its standard procedures with this particle-based on Eq. (18) and Eq. (19). In the subsequent evaluating phase, fitness function estimations and range restrictions are verified for all fireflies and particles. If the maximum iteration limit is attained, the hybrid method will be halted, and (g_{best}) and its fitness value can be represented as output of the developed hybrid method. A maximum number of fitness function estimation (Max_{Fes}) is exploited. Max_{Fes} is a well-liked termination condition which is permitted the maximum computation of objective models in evolutionary computing algorithms. In PSO, the inertia weight (w) parameter aids to balance among exploitation a well as exploration. A linear decreasing inertia weight is used and computed based on Eq. (20). Minimum and maximum velocities of a particle (U_{min}, U_{max}) are used to restrict subsequently distance in a direction. They are arbitrarily ready at the start of the developed method in the velocity range.

5. Results and Discussions

5.1. Experimental Procedure

In this work, to show performance analysis of developed algorithms, 33-bus and 69- bus test systems were exploited and the proposed method was compared with the Artificial Bee Colony (ABC), Simulated Annealing (SA), and Whale Optimization Algorithm (WOA). The substation voltage magnitude was exploited and available DG size that injects reactive power for both the test systems.

5.2. Performance Analysis

Tables 1 and 2 summarize the analysis of the developed and existing methods for both the IEEE 33 and 69 bus systems. Here, the overall analysis exhibits the performance of the developed technique is superior to conventional methods. Tables 3 and 4 summarize the analysis for IEEE 33 and 69 bus systems for two test cases.

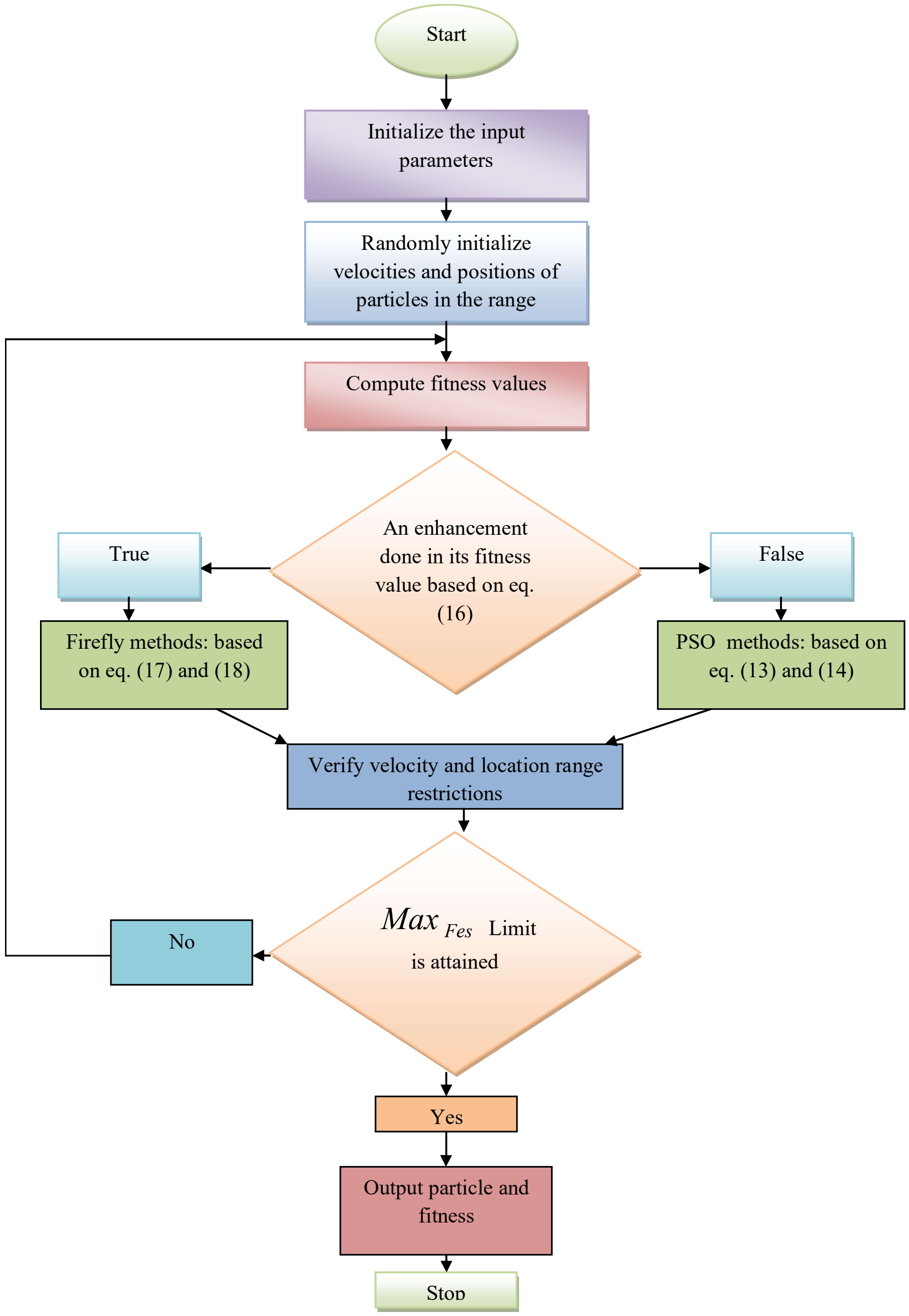

Fig. 1. *Flow chart of the proposed model*

Table 1. *Analysis for developed and existing methods of IEEE 33 bus system*

Algorithms	DG size	location	Power loss (kW)	Minimum voltage in pu (bus)	Net savings ($/year)	% reduction in power loss	Total operating cost ($/year)	% savings
SA	1111.4	5	81.04	0.9577	55,754	51.11	51,545	51.58
	487.4	18						
	857.9	50						
WOA	551.1	14	89.89	0.9705	54,570	57.4	54,709	49.98
	198.4	18						
	1057.1	51						
ABC	514.7	14	90.59	0.9557	54,840	57.01	54,559	50.17
	104.9	18						
	1055	51						
Proposed method	1071.85	50	75.75	0.9588	70,545	55.05	58,754	54.5
	771.488	15						
	855.578	15						

Table 2. *Analysis for developed and existing methods in IEEE 33 bus system*

Algorithms	DG size	location	Power loss (kW)	Minimum voltage in pu (bus)	Net savings ($/year)	% reduction in power loss	Total operating cost ($/year)	% savings
SA	630.6	19	77.09	0.976	79,763	65.73	59,179	57.93
	1331.1	60						
	639.9	65						
WOA	395.6	37	75.31	0.9909	91,363	66.56	56,559	59.99
	667.6	65						
	1365.1	61						
ABC	339.1	37	76.13	0.9793	91,356	66.16	56,667	59.91
	633.6	65						
	1336.6	61						
Proposed method	699.03	11	99.71	0.979	91,960	99	55,991	59.61
	676.69	19						
	1690.3	61						

Table 3*. Analysis In IEEE 33 bus system*

	Uncommon -nsated	Compensated									
Optimal location and sizing of DG		**Type -1 DG**				**Type -2 DG**					
		Single		**Multiple**		**Single**			**Multiple**		
	–	41	1854.1	11	488.02	41	1811.8	1414.4	41	1580.52	1044.04
				18	474.48	21	281.44	224.48	21	281.44	224.48
				41	1480.4				11	484.4	444.02
DG total size			1854.1		2445.8		1811.8	1414.4		2555.2	1424.5
Total R_{loss}	224.82	84.18		48.72		24.15			5.44		
Total S_{loss}	102.14	40.54		45.05		14.48			7.44		
%Minimization in R_{loss}		44.02		48		88.71			87.48		
%Minimization in S_{loss}		40.4		45.48		85.82			82.82		
Least Voltage	0.8082	0.8482		0.878		0.8725			0.8821		
Operation cost	1,47,821	40,284		55,881		24,527			14,445		
Net savings	–	77,444		81,840		1,14,484			1,21,285		
%savings	–	54.28		58.41		82.84			87.84		

Table 4.*Analysis in IEEE 69 bus system*

	Uncompen sated	Compensated									
Optimal location and sizing of DG		**Type -1 DG**				**Type -2 DG**					
		Single		**Multiple**		**Single**			**Multiple**		
	-	7	1689.7	31	1171.83	7	1667.7	1771	17	1179.38	711.811
				16	771.788				13	881.88	777.117
				13	867.778				31	963.71	761
DG total size			1689.7		1711.997		1667.7	1771		3117.88	1997.838
Total R_{loss}	111.99	111		73.76		77.87		17.18			
Total S_{loss}	173.11	81.79		61.13		67.83		11.88			
%Minimizatio n in R_{loss}	–	77.39		76.16		77.87		91.18			
%Minimizatio n in S_{loss}	–	71.91		77.37		71.79		91			
Least Voltage	1.9138	1.9717		1.9788		1.9683		1.9917			
Operation cost	1,19,379	81,113		68,737		67,711		16,718			
Net savings	–	78,377		71,776		77,767		1,13,771			
%savings	–	37.38		67.7		67.7		81.11			

6. Conclusion

In this article, a hybrid PSO-FF technique was developed to decide optimal sizing and placement of Distributed Generators in RDS. Here, optimization issues possess multi objectives namely minimization of power loss, minimization of operating cost and enhancement of voltage profile. Moreover, the developed approach was examined on 33-bus and 69-bus test systems for 2 cases such as case-1 and 2 namely Type-1: DG positioning and Type-2 DG positioning. Finally, outcomes attained from the recommended method were evaluated with other renowned optimization methods, and it reveals the effectiveness of the developed method for multi objectives and multi constraints.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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