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Solution of optimal reactive power dispatch by Lévy-flight phasor particle swarm optimization

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ABSTRACT

Optimal reactive power dispatch (ORPD) problems are important tools for the sake of security and economics of power systems. The ORPD problems are nonlinear optimization problems to minimize the real power losses and voltage profile enhancement by optimizing several discrete and continuous control variables. This paper proposes a Lévy-flight phasor particle swarm optimization (LPPSO) for solving ORPD problems while considering real power losses and voltage profile in two standard power systems. The simulation results demonstrate that the LPPSO algorithm proves itself as an acceptable method for reaching a more optimal solution for the ORPD problems.

1. Introduction

Optimal reactive power dispatch (ORPD) problems are essential tools in power systems' operation and security considerations. ORPD problems minimize system active power losses by optimally determining parameters like the generator voltage magnitudes (continuous variables), transformers' tap ratios, and compensations by shunt compensating devices (discrete variables) while satisfying a number of equality and inequality constraints. This problem is a mixed integer, non-linear optimization problem, having a large number of local optima.

Recently, researchers have explored various optimization methods and intelligent algorithms to address ORPD problems. For instance, (Siyuan & Suwen, 2017) proposes an enhanced genetic algorithm (IGA) for the IEEE14 node system that improves several aspects such as coding method, fitness function, initial population generation, crossover, and mutation strategy. Results indicate that IGA improves convergence speed, ability, and reduces power loss. Similarly, (Pattanaik et al., 2019) experiments with improved real-coded GA (IRCGA) on different systems and observes that IRCGA outperforms other evolutionary methods. In Mandal and Roy (2013), to enhance solution quality and accelerate convergence speed, researchers incorporated the quasi-opposition based learning (QOBL) concept in original TLBO algorithm for solving multi-objective ORPD (MOORPD) problem by minimizing real power loss, voltage deviation, and voltage stability index. In Zare et al. (2014), researchers propose the MBSO algorithm for probabilistic reactive power and voltage control in distribution networks. Other methods such as fuzzy TLBO (Moghadam & Seifi, 2014), Gaussian bare-bones TLBO (GBTLBO) algorithm, and its modified version (MGBTLBO) (Ghasemi et al., 2015), and a hybrid optimization algorithm of particle swarm optimization (PSO) and gravitational search algorithm (GSA) (Radosavljević et al., 2015). The Self-organizing migrating algorithm with quadratic interpolation (SOMAQI) was also used for solving large-scale Optimal Reactive Power Dispatch (ORPD) (Singh & Agrawal, 2016). Another approach is the improved pseudo-gradient search-PSO (IPG-PSO) (Polprasert et al., 2016). Three different PSO variants were also used to solve the economically evaluated ORPD (EORPD) (Sarstedt et al., 2018). The gray wolf optimizer (GWO) algorithm (Sulaiman et al., 2015) and its hybrid version (HGWO) by incorporating crossover operator (Parekh & Suthar, 2019) were also used for solving the problem. The multi-objective differential evolution (MODE) algorithm was applied to solve the voltage stability constrained ORPD (VSCRPP) problem (Preetha Roselyn et al., 2014; Basu, 2016). Additionally, a hybrid PSO and DE were used to solve ORPD in both normal and contingency cases (Nguyen & Dao, 2019). Biogeography-based optimization

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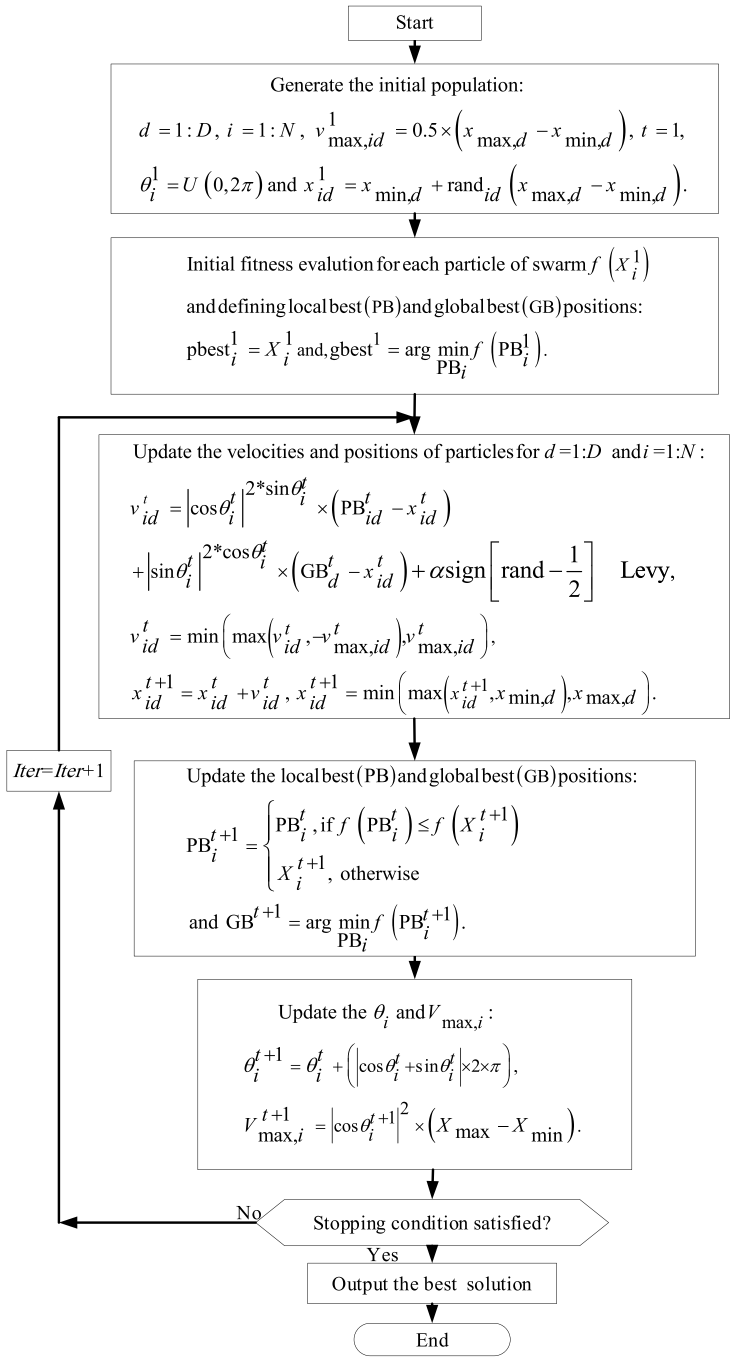

Fig. 1. Flowchart of LPPSO algorithm.

(BBO) was utilized to solve the ORPD problem in the IEEE 30-bus system with multiple FACTS devices (Roy et al., 2011). The backtracking search optimization (BSO) (Shaheen et al., 2018) was also exploited to solve ORPD in standard and real test systems. Different developed GSA algorithms were used to achieve the optimal value of loss, voltage deviation, and voltage stability index (Roy et al., 2012; Niknam et al., 2013; Shaw et al., 2014). A multi-objective evolutionary algorithm (MOEA) technique based on Pareto optimality was also applied (Hongxin et al., 2013). The artificial bee colony algorithm (ABC) was shown to converge to better solutions and much faster than the earlier reported approaches (Ettappan et al., 2020). The improved harmony search (IHS) algorithms was applied for solving conventional ORPD with static var compensator (SVC) (Karthikaikannan & Sundarabalan, 2017). Hybrid algorithms combining firefly algorithm (FA) and shuffled frog leaping algorithm (SFLA) algorithms with Nelder Mead (NM) simplex method were developed in (Rajan & Malakar, 2015; Khorsandi et al., 2011). The JAYA algorithm was proven effective for solving ORPD on three standard systems (Das & Roy, 2018; Barakat et al., 2018). The seeker optimization algorithm (SOA) which is based on the concept of simulating the act of human searching was proposed (Dai et al., 2009; Shahbazi & Kalantar, 2013; Dai et al., 2009) for solving the ORPD problem. The hybrid and Gaussian bare-bones imperialist competitive algorithm (ICA) were also used for solving ORPD problems on standard test systems (Ghasemi et al., 2014; Ghasemi et al., 2015). Multi-group search optimizer (MGSO) demonstrated superior performance for solving ORPD in high-dimensional test systems (Zhou et al., 2014). Gaussian bare-bones water cycle algorithm (GBBWCA) (Heidari et al., 2017), atmosphere clouds model (ACM) algorithms (Kanagasabai et al., 2014), bacteria

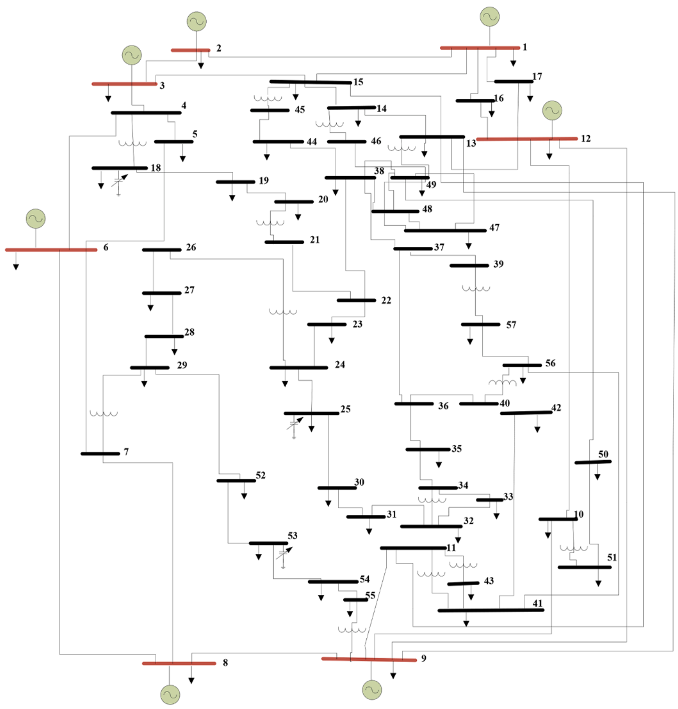

Fig. 2. Single line diagram of IEEE 57-bus power system.

foraging algorithm (BFA) (Tripathy & Mishra, 2007), multi-objective adaptive immune algorithm (MOAIA) (Xiong et al., 2008), and a novel fuzzy adaptive heterogeneous comprehensive-learning PSO (FAHCLPSO) algorithm (Naderi et al., 2017) were also applied for solving the ORPD problems. Additionally, the exchange market algorithm (EMA) demonstrated superior computational efficiency and robustness (Rajan & Malakar, 2016), while the chaotic krill herd algorithm (CKHA) improved effectiveness, quality of solution, and convergence speed (Mukherjee & Mukherjee, 2016). The real GA (RGA) combined with an interior point method (IPM) solved the simultaneous transmission network expansion and reactive power planning problem (TEPRPP) via an AC model (Mahmoudabadi & Rashidinejad, 2013). A new multi-objective strategy incorporating fuzzy set theory was also proposed (Ghasemi et al., 2014). Coulomb's and Franklin's laws algorithm (CFA) yielded a better solution compared to other state-of-the-art methods (Ghasemi et al., 2022). Modified ant-lion optimizer (ALO) (MALO) was shown to intelligently balance both exploration and exploitation (Mouassa et al., 2017), while an improved ALO (IALO) algorithm was demonstrated as more effective than ALO in terms of the most optimal solution search ability, solution search speed, and search stabilization (Li et al., 2019).

Recent advancements in optimization algorithms have significantly enhanced the performance of solving complex engineering design problems (Rahimnejad et al., 2023; Ghasemi et al., 2023a, 2023b). The study discussed in Hosseini-Hemati et al. (2021) focused on analyzing the influence of load models on the multi-objective ORPD problems in active distribution networks. A chaotic turbulent flow of water-based optimization (CTFWO) algorithm were proposed in Abd-El Wahab et al. (2022) for solving the ORPD problem. The experimental results demonstrated that the proposed TFWO algorithms performed exceptionally well and were competitive with numerous state-of-the-art algorithms. In Alghamdi (2022), a novel and effective θ-self-adaptive teaching and learning technique was used to propose an enhanced Teaching-Learning Based Optimization (TLBO) algorithm to optimize voltage and active loss management in power networks. Additionally,

Table 1
Statistical details for IEEE 57-bus power system.

Methods	Active power losses (p.u.)					Voltage deviation (p.u.)			
	ω_1= 1,ω_2= 0					ω_1= 0,ω_2= 1			
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	0.245011	0.246099	0.245391	4.33×10^{-4}	13.92	0.7373	0.8265	0.8141	4.68×10^{-2}
FPSO	0.245682	**0.246003**	0.245828	5.03×10^{-4}	13.68	0.7364	**0.8066**	0.7878	5.75×10^{-2}
CLPSO	0.245445	0.248009	0.246365	4.52×10^{-4}	13.76	0.7768	0.8771	0.8251	9.29×10^{-2}
APSO	0.246787	0.24996	0.247367	6.1×10^{-4}	13.29	0.7870	0.8382	0.8222	8.22×10^{-2}
PPSO	0.24464	0.246568	0.24506	3.95×10^{-4}	14.05	0.7612	0.8304	**0.7784**	5.85×10^{-2}
LPPSO	**0.244198**	0.247135	**0.24505**	$\mathbf{3.11\times 10^{-4}}$	**14.2**	**0.7285**	0.8208	**0.7784**	$\mathbf{3.48\times 10^{-2}}$
ω_1= 0.5,ω_2= 0.5									
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	0.261263	0.294557	0.286035	4.45×10^{-3}	8.21	0.7486	0.9554	0.9008	3.41×10^{-1}
FPSO	0.261296	0.318733	0.283688	6.88×10^{-2}	8.19	0.7777	0.8553	0.8176	5.04×10^{-2}
CLPSO	0.261676	0.27472	0.267657	9.64×10^{-4}	8.06	0.7634	0.8755	**0.8008**	9.16×10^{-3}
APSO	0.261997	0.282613	0.271258	5.95×10^{-3}	7.95	0.7665	0.8932	0.8182	4.42×10^{-2}
PPSO	0.259994	**0.267489**	0.262788	2.17×10^{-3}	8.65	0.7678	0.8484	0.8018	7.67×10^{-3}
LPPSO	**0.257411**	0.274632	**0.261742**	$\mathbf{8.87\times 10^{-4}}$	**9.56**	**0.7426**	**0.8468**	0.8014	$\mathbf{3.3 \times 10^{-3}}$
ω_1= 0.75,ω_2= 0.25									
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	0.258404	0.289064	0.268696	4.12×10^{-3}	9.21	0.8043	0.8643	0.8215	7.34×10^{-3}
FPSO	0.260318	0.289446	0.267407	7.17×10^{-3}	8.54	0.8040	0.9137	0.8635	3.19×10^{-2}
CLPSO	0.261285	0.288236	0.272145	8.27×10^{-3}	8.2	0.7875	0.8683	0.8886	9.93×10^{-3}
APSO	0.26258	0.275047	0.26756	3.66×10^{-3}	7.74	0.7700	0.8658	0.8195	6.46×10^{-2}
PPSO	0.258545	0.274612	0.263501	5.58×10^{-3}	9.16	0.7833	1.0688	0.926	6.05×10^{-2}
LPPSO	**0.256396**	**0.263633**	**0.258209**	$\mathbf{7.93\times 10^{-4}}$	**9.92**	**0.7530**	**0.8323**	**0.8072**	$\mathbf{2.12\times 10^{-2}}$
ω_1= 0.25,ω_2= 0.75									
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	0.267547	0.289369	0.270653	4.21×10^{-3}	6.0	0.7629	0.8449	0.8246	8.75×10^{-3}
FPSO	0.277426	0.285136	0.279924	2.69×10^{-3}	2.53	0.7516	0.8938	0.8471	1.7×10^{-2}
CLPSO	0.264816	0.285036	0.276313	5.09×10^{-3}	6.96	0.7993	0.8834	0.8588	$\mathbf{3.38\times 10^{-3}}$
APSO	0.272005	0.290706	0.280185	3.62×10^{-2}	4.43	0.8086	0.8809	0.8391	8.19×10^{-2}
PPSO	0.263987	0.286067	0.270615	8.73×10^{-3}	7.25	0.7714	0.8335	0.7816	2.95×10^{-2}
LPPSO	**0.262396**	**0.278974**	**0.269724**	$\mathbf{5.47\times 10^{-4}}$	**7.81**	**0.7312**	**0.8293**	**0.7844**	5.24×10^{-3}

Table 2
Best control variables settings (p.u.) for active power loss minimization in IEEE 57-bus power system.

Variable	BBO (Bhattacharya and Chattopadhyay, 2009)	NSGA-II (Ghasemi et al., 2015)	VEPSO (Ghasemi et al., 2015)	GSA (Roy et al., 2012)	IWO (Ghasemi et al., 2014)	BSO (Shaheen et al., 2018)	PPSO (Ghasemi et al., 2019)	**LPPSO**
V_{G1}	1.06	1.0558	1.06	1.06	1.06	1.0724	1.06	**1.06**
V_{G2}	1.0504	1.049	1.0524	1.0553	1.05912	1.057	1.056	**1.0586**
V_{G3}	1.044	1.0306	1.0383	1.0348	1.04716	1.0372	1.0374	**1.0465**
V_{G6}	1.0376	1.0148	1.0301	1.0246	1.03817	1.0328	1.0353	**1.0355**
V_{G8}	1.055	1.0419	1.0542	1.0418	1.05926	1.0603	1.0594	**1.0495**
V_{G9}	1.0229	1.0148	1.0213	1.0253	1.02729	1.0283	1.0261	**1.0295**
V_{G12}	1.0323	1.0349	1.0312	1.0232	1.0374	1.041	1.0359	**1.0433**
T_{4-18}	0.96693	1.01	1.01	0.9348	1.05	1.01	0.92	**0.95**
T_{4-18}	0.99022	0.97	0.97	0.9939	1.0	0.97	1.01	**1.0**
T_{21-20}	1.012	1.08	1.02	1.0017	1.07	1.02	1.01	**1.02**
T_{24-26}	1.0087	1.04	1.03	1.0058	1.02	1.02	1.01	**1.01**
T_{7-29}	0.97074	0.96	0.97	0.9681	0.97	0.99	0.97	**0.97**
T_{34-32}	0.96869	0.95	0.93	0.9718	0.99	0.96	0.98	**0.98**
T_{11-41}	0.90082	0.93	0.91	0.9008	0.9	0.94	0.9	**0.9**
T_{15-45}	0.96602	0.96	0.96	0.9604	0.96	0.97	0.96	**0.96**
T_{14-46}	0.95079	0.95	0.95	0.9476	0.95	0.96	0.95	**0.95**
T_{10-51}	0.96414	0.96	0.98	0.9571	0.98	0.98	0.96	**0.96**
T_{13-49}	0.92462	0.91	0.92	0.9195	0.93	0.94	0.92	**0.92**
T_{11-43}	0.95022	0.97	0.95	0.9477	0.99	0.95	0.95	**0.96**
T_{40-56}	0.99666	1.02	1.01	1.0017	1.01	1.01	0.99	**0.99**
T_{39-57}	0.96289	1.01	0.99	0.9621	1.04	0.98	0.99	**0.96**
T_{9-55}	0.96001	0.97	0.97	0.9628	0.96	0.98	0.96	**0.99**
Q_{C18} (p.u.)	0.09782	0.08	0.08	0.0898	0.0442	0.088	0.1	**0.1**
Q_{C25} (p.u.)	0.058991	0.03	0.04	0.0588	0.0433	0.059	0.06	**0.06**
Q_{C53} (p.u.)	0.06289	0.02	0.01	0.063	0.0615	0.052	0.06	**0.06**
P_{loss} (p.u.)	0.24544	0.252599	0.248955	0.24439	0.245939	0.244492	0.24464	**0.244198**

Table 3
Best control variables settings (p.u.) for voltage deviation minimization in IEEE 57-bus power system.

Variable	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PPSO	**LPPSO**	Variable	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PPSO	**LPPSO**
V_{G1}	1.06	1.0290	1.05999	**1.0064**	T_{11-41}	0.9000	0.9155	0.9	**0.91**
V_{G2}	1.0414	1.0129	1.05082	**0.94**	T_{15-45}	0.9668	0.9633	0.97	**0.93**
V_{G3}	1.0169	1.0123	1.04533	**1.0296**	T_{14-46}	0.9	0.9482	0.95	**0.99**
V_{G6}	0.9956	1.0079	1.04094	**0.9972**	T_{10-51}	0.9748	0.9566	0.96	**1.0**
V_{G8}	0.9915	1.0366	1.05984	**1.0456**	T_{13-49}	0.9	0.9568	0.92	**0.92**
V_{G9}	0.9670	1.0059	1.02551	**1.0142**	T_{11-43}	0.9	0.9534	0.95	**0.98**
V_{G12}	0.9935	1.0285646	1.03209	**1.0267**	T_{40-56}	1.0262	0.9653	1.02	**0.94**
T_{4-18}	0.9100	0.9743	0.96	**0.95**	T_{39-57}	0.9	1.0053	0.97	**0.92**
T_{4-18}	1.0291	0.9610	0.99	**1.06**	T_{9-55}	0.9266	0.9808	0.97	**1.0**
T_{21-20}	0.9801	0.9963	1.01	**0.97**	Q_{C18} (p.u.)	0.0	0.069827	0.1	**0.07**
T_{24-26}	1.0134	1.0251	1.01	**1.09**	Q_{C25} (p.u.)	0.1	0.086683	0.06	**0.06**
T_{7-29}	0.9622	0.9602	0.98	**0.94**	Q_{C53} (p.u.)	0.1	0.048687	0.063	**0.01**
T_{34-32}	0.9170	0.9149	0.98	**0.91**	VD	0.7952	0.8007	0.7693	**0.7285**

the Symbiotic Organisms Search (SOS) method was employed in Prasad et al. (2022) to solve the ORPD problem and was found to be superior to other methods cited in the literature.

This paper proposes a new version of phasor particle swarm optimization (PPSO) (Ghasemi et al., 2019) improved with Lévy flight, named Lévy-flight phasor particle swarm optimization (LPPSO), for solving different ORPD problems with complex objective functions in the power systems. In PPSO, the particle control parameters are modeled using a phasor angle (θ) based on the phasor theory which results in achieving better optimization performance compared to using fixed control parameters. The algorithm was successfully implemented for solving real-world engineering problems such as economic dispatch (Gholamghasemi et al., 2019) and optimal placement and sizing of distributed generation (Ullah et al., 2019).

The ORPD problems are highly intricate and difficult to solve due to their non-linear and non-convex nature. Despite the availability of other optimization algorithms, they still need improvements such as enhanced robustness, avoidance of local optima, better solutions, and improved convergence characteristics. In light of this, the present research aims to address these gaps and improve the quality of optimal solutions by strategically utilizing Lévy-flight to enhance the performance of PPSO. The study proposes a novel and robust algorithm called LPPSO, which combines the power of Lévy-flight and phasor particle swarm optimization algorithm for various ORPD problems in large-scale IEEE 57-bus power and IEEE 118-bus power systems. The paper contributes to the field in five ways:

1. Developing a novel and robust optimization algorithm called LPPSO by combining Phasor and Lévy-flight particle swarm optimization

Table 4
Statistical details for active power loss minimization in IEEE 57-bus power system.

Algorithms	Mean (p.u.)	Worst (p.u.)	Best (p.u.)	Time (*sec*)	%Psave	Std.
ICA (Ghasemi, 2017)	0.2538722	0.2554803	0.244799	44.32	13.9909	8.0561e-3
DE (Zhang et al., 2010)	0.255509	N.R.	0.250862	152.0557	11.8607	3.003e-3
CGA (Zhang et al., 2010)	0.264826	N.R.	0.248853	176.6708	12.5666	6.671e-3
SCA (Abdi et al., 2021)	N.R.	N.R.	0.2540635	N.R.	N.R.	N.R.
SGA (Khazali and Kalantar, 2011)	0.268378	0.277651	0.2564	N.R.	N.R.	N.R.
PSO (Khazali and Kalantar, 2011)	0.264742	0.270576	0.2503	N.R.	N.R.	N.R.
HSA (Khazali and Kalantar, 2011)	0.25924	0.269653	0.249059	N.R.	N.R.	N.R.
SPSO-07 (Dai et al., 2009)	0.2475227	0.2545745	0.2443043	137.35	14.1647	2.833e-3
CGA (Dai et al., 2009)	0.2629356	0.2750772	0.2524411	411.38	11.3059	6.2951e-3
MGBICA (Ghasemi et al., 2015)	N.R.	N.R.	0.248863	N.R.	N.R.	N.R.
PSO (Mehdinejad et al., 2016)	N.R.	N.R.	0.247742	927	N.R.	N.R.
CLPSO (Zhang et al., 2010)	0.256381	N.R.	0.250684	104.4016	11.9233	3.601e-3
CLPSO (Dai et al., 2009)	0.2467307	0.2478083	0.245152	426.85	13.8669	9.3415e-4
L-SACP-DE (Dai et al., 2009)	0.310326	0.3697873	0.2791553	428.98	1.92	3.2232e-2
AGA (Zhang et al., 2010)	0.253251	N.R.	0.244857	165.8703	13.9706	6.635e-3
L-DE (Dai et al., 2009)	0.3317783	0.4190941	0.2781264	431.41	2.2815	4.7072e-2
AGA (Dai et al., 2009)	0.2512784	0.2676169	0.2456484	449.28	13.6925	6.0068e-3
BSO-3 (Shaheen et al., 2018)	0.24944	0.260097	0.244492	N.R.	N.R.	3.32e-3
BSO-5 (Shaheen et al., 2018)	0.2509	0.2569	0.24640	N.R.	N.R.	2.64e-3
WCA (Kien et al., 2021)	0.265319	N.R.	0.260402	27.4	N.R.	N.R.
SFOA (Kien et al., 2021)	0.284249	N.R.	0.266541	21.3	N.R.	N.R.
MOPSO—CD (Ghasemi et al., 2015)	N.R.	N.R.	0.248914	N.R.	N.R.	N.R.
iTDEA (Ghasemi et al., 2015)	N.R.	N.R.	0.24938	N.R.	N.R.	N.R.
NKEA (Ghasemi et al., 2015)	N.R.	N.R.	0.250113	N.R.	N.R.	N.R.
GDE3 (Ghasemi et al., 2015)	N.R.	N.R.	0.250946	N.R.	N.R.	N.R.
BSO-1 (Shaheen et al., 2018)	0.25099	0.26265	0.24536	N.R.	N.R.	3.75e-3
GBICA (Ghasemi et al., 2015)	N.R.	N.R.	0.249666	N.R.	N.R.	N.R.
COA (Kien et al., 2021)	0.268983	N.R.	0.245358	23.2	N.R.	N.R.
JGGA (Ghasemi et al., 2015)	N.R.	N.R.	0.249124	N.R.	N.R.	N.R.
NSGA-II (Ghasemi et al., 2015)	N.R.	N.R.	0.252599	N.R.	N.R.	N.R.
OMOPSO (Ghasemi et al., 2015)	N.R.	N.R.	0.252417	N.R.	N.R.	N.R.
VEPSO (Ghasemi et al., 2015)	N.R.	N.R.	0.248955	N.R.	N.R.	N.R.
BSO-2 (Shaheen et al., 2018)	0.249935	0.256244	0.244856	N.R.	N.R.	2.76e-3
SSA (Kien et al., 2021)	0.270306	N.R.	0.253854	21.8	N.R.	N.R.
PPSO	0.256284	0.268420	0.24464	29.11	14.05	$6.73\times 10-2$
LPPSO	0.24505	0.247135	0.244198	28.45	14.2	$3.11\times 10-4$

algorithm for optimizing ORPD problems concerning power loss minimization and voltage deviation minimization.
2. Based on the simulation results, the proposed hybridization approach significantly enhances the ability of the PPSO algorithm to escape local optimums due to their rapid convergence speed.
3. The study introduces an enhanced operator to update the population to increase the power of the local search of the original PPSO algorithm.
4. The paper provides optimal scheduling of global solutions for various high-dimensional ORPD problems of large-scale power systems, including the IEEE standard 57-bus and 118-bus test systems.
5. The proposed LPPSO algorithm requires a considerably smaller initial population size, which saves computational time.

The remainder of this paper is categorized as: The 2nd section explains the formulation of the typical ORPD problems. The PSO, PPSO, and LPPSO algorithms are introduced in Section 3. Then, the optimization results and discussions are presented in Section 4. Finally, the conclusions are presented in the last section. From now on, the expressions “active power losses”, “real power losses” and “power losses” are used interchangeably.

2. Formulation of ORPD problems

Generally, the goal of ORPD problems (or Volt/VAR optimal control) is to minimize the active power losses (P_{loss}) through optimizing power system control parameters subject to a number of equality and inequality constraints (Deeb & Shahidehpour, 1990; Lo & Zhu, 1991; Ramesh et al., 2012; Quintana & Santos-Nieto, 1989).

2.1. General structure of ORPD problem

The mathematical model of the ORPD problem is as follows:

$$\text{Min}: J(x,u) \tag{1}$$

$$\text{Subjectto}: g(x,u) = 0 \tag{2}$$

$$h(x,u) \leq 0 \tag{3}$$

Where, *J(x, u)* is the objective function (OF), and *x* is the vector of state variables which consists of:

1. V_L (the voltage of load buses).
2. Q_G (the reactive power generation by generating units).
3. S_l (the apparent power flow through the transmission lines).

Therefore, the state vector x can be shown as follows:

$$x = [V_{L1}, \ldots V_{LNPQ}, Q_{G1}, \ldots Q_{GNG}, S_{l1}, \ldots S_{lNTL}]^T \tag{4}$$

where *NG, NPQ, and NTL* are the numbers of generating units, load buses, and transmission lines, respectively.
u is the control variables' vector comprising:

1. V_G (the generation bus voltage).
2. T (the transformers' tap settings).
3. Q_C (the reactive power (or VAR) shunt compensation).

Hence, *u* may be described as:

$$u^T = [V_{G1} \ldots V_{GNG}, Q_{C1} \ldots Q_{CNC}, T_1 \ldots T_{NT}] \tag{5}$$

Table 5
Statistical details for voltage deviation minimization in IEEE 57-bus power system.

Algorithms	Mean (p.u.)	Worst (p.u.)	Best (p. u.)	Times (*sec*)	Std.
OMOPSO (Ghasemi et al., 2015)	N.R.	N.R.	0.86747	N.R.	N.R.
PSO (Mehdinejad et al., 2016)	N.R.	N.R.	0.7593	N.R.	N.R.
VEPSO (Ghasemi et al., 2015)	N.R.	N.R.	0.80558	N.R.	N.R.
JGGA (Ghasemi et al., 2015)	N.R.	N.R.	0.87169	N.R.	N.R.
GDE3 (Ghasemi et al., 2015)	N.R.	N.R.	0.80185	N.R.	N.R.
NSGA-II (Ghasemi et al., 2015)	N.R.	N.R.	0.86363	N.R.	N.R.
iTDEA (Ghasemi et al., 2015)	N.R.	N.R.	0.79468	N.R.	N.R.
ICA (Mehdinejad et al., 2016)	N.R.	N.R.	0.7759	N.R.	N.R.
MOPSO—CD (Ghasemi et al., 2015)	N.R.	N.R.	0.81807	N.R.	N.R.
NKEA (Ghasemi et al., 2015)	N.R.	N.R.	0.78923	N.R.	N.R.
GBICA (Ghasemi et al., 2015)	N.R.	N.R.	0.7749	N.R.	N.R.
TLBO (Alghamdi, 2022)	0.7883	0.7925	0.7856	41.89	6.195e-2
SALTLBO (Alghamdi, 2022)	0.7529	0.7566	0.7507	45.17	8.709e-3
SACTLBO (Alghamdi, 2022)	0.7665	0.7684	0.7624	44.96	5.007e-3
SSA (Kien et al., 2021)	1.1736	N.R.	0.94	20.9	N.R.
WCA (Kien et al., 2021)	0.7913	N.R.	0.7309	27.2	N.R.
MGBICA (Ghasemi et al., 2015)	N.R.	N.R.	0.77461	N.R.	N.R.
SFO (Kien et al., 2021)	0.9975	N.R.	0.7913	21.1	N.R.
PPSO	0.7784	0.8304	0.7612	23.15	5.85× 10−2
LPPSO	0.7784	0.8208	0.7285	23.78	3.48× 10−2

where *NT* and *NC* are the numbers of tap-changing transformers and reactive power compensating units, respectively.

2.2. Objective functions for reactive power optimal control

2.2.1. Minimizing real power losses

The main objective of the ORPD problem is to minimize the total active transmission losses, which can be formulated as follows:

$$f_1(x,u) = P_{loss} = \sum_{\substack{k=1 \\ k=(i,j)}}^{NTL} g_k\left(V_1^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}\right) \quad (6)$$

where P_{loss} is the total active transmission losses, g_k is the conductance of branch *k*, V_i and V_j are the voltages of *i*th and *j*th buses, respectively, and δ_{ij} is the phase difference of voltages between buses *i* and *j*.

2.2.2. Minimizing voltage magnitude deviation

The OF for minimizing voltage deviation (*VD*) is formulated as below:

$$f_2(x,u) = VD = \sum_{i=1}^{NPQ} |V_i - 1.0| \quad (7)$$

where *VD* is the summation of bus voltage magnitude deviations of all buses.

2.3. Constraints

2.3.1. Equality constraints

In solving the ORPD problem, the power balance equations should be satisfied at all buses, which are stated as follows:

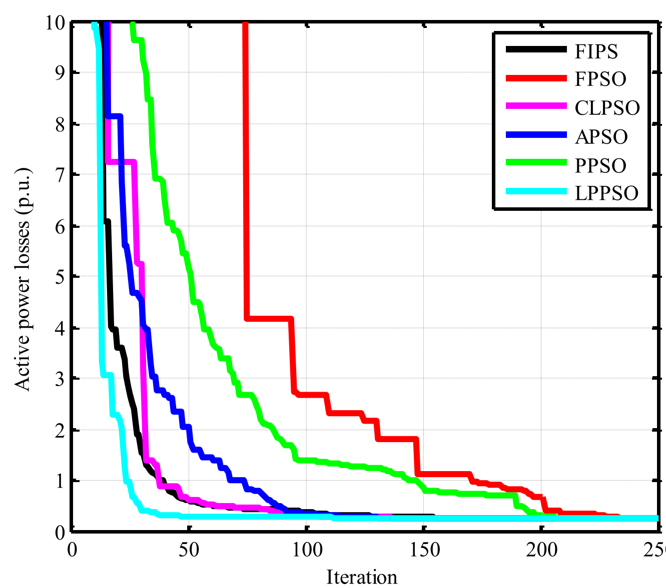

Fig. 4. Convergence characteristics of different PSO algorithms for active power loss minimization in IEEE 57-bus power system.

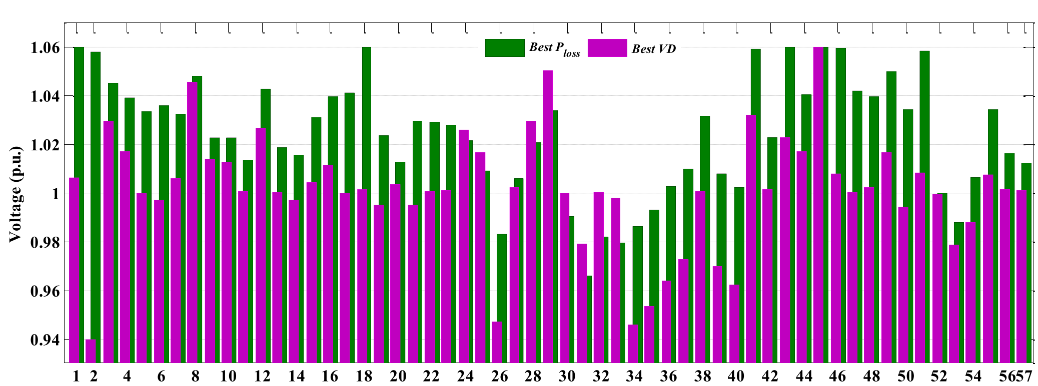

Fig. 3. Voltage profiles of the best solutions for IEEE 57-bus power system.

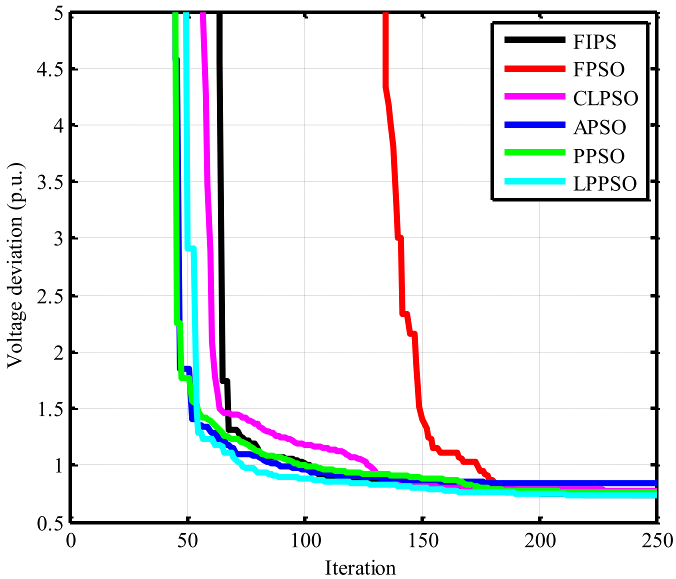

Fig. 5. Convergence characteristics of different PSO algorithms for voltage deviation minimization in IEEE 57-bus power system.

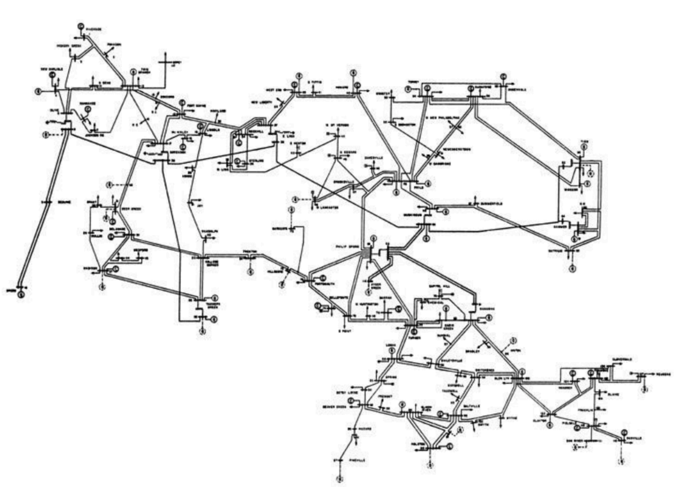

Fig. 6. Single line diagram of IEEE 118-bus large-scale test power system (Mallipeddi et al., 2012).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij}\cos\left(\delta_{ij}\right) + B_{ij}\sin\left(\delta_{ij}\right) \right] = 0 \quad (8)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij}\sin\left(\delta_{ij}\right) - B_{ij}\cos\left(\delta_{ij}\right) \right] = 0 \quad (9)$$

where NB is the number of all buses, P_{Gi} and P_{Di} are the active power generation and demand, respectively, Q_{Gi} and Q_{Di} are the reactive generation and demand, respectively, G_{ij} is conductance and B_{ij} is susceptance.

2.3.2. Inequality constraints

These constraints include:

i. Constraints pertaining to generators: the real power generation of the generator at reference bus, voltage magnitude of generator buses, and reactive power generations must be limited between their corresponding limits as:

$$\begin{aligned} & P_{G,slack}^{\min} \le P_{G,slack} \le P_{G,slack}^{\max} \\ & V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \quad i = 1, \dots, NG \\ & Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \quad i = 1, \dots, NG \end{aligned} \quad (10)$$

where $V_{Gi}^{\min}$and $V_{Gi}^{\max}$ are the lower and upper limits of the ith generator, respectively; $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ the lower and upper limits of the real power output of the ith generator, respectively; and $Q_{Gi}^{\min}$and $Q_{Gi}^{\max}$are the lower and upper limits of reactive power generation of the ith generator, respectively.

ii. Constraints pertaining to transformers: transformer taps can only be set in a permissible range, as:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \dots, NT \quad (11)$$

where $T_i^{\min}$ and $T_i^{\max}$ are the lower and upper bounds of ith transformer's tap settings.

iii. Constraints pertaining to shunt VAR compensators: The outputs of these compensators must be between their permissible limits as:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i = 1, \dots, NC \quad (12)$$

where $Q_{Ci}^{\min}$and $Q_{Ci}^{\max}$are the lower and upper limits of ith reactive power compensator.

iv. Security constraints: including the limits of load bus voltages and transmission branch loadings as:

Table 6
Statistical details for IEEE 118-bus power system.

Methods	Active power losses (p.u.)					Voltage deviation(p.u.)			
	ω_1= 1,ω_2= 0					ω_1= 0,ω_2= 1			
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	1.163125	1.176519	1.168817	6.94×10^{-2}	12.78	0.1498	0.1655	0.1557	6.92×10^{-2}
FPSO	1.161321	1.165864	1.162413	1.05×10^{-3}	12.92	0.1517	0.1569	0.153	1.12×10^{-3}
CLPSO	1.151499	1.170063	1.163832	8.8×10^{-2}	13.65	0.1441	0.168	0.1527	4.49×10^{-2}
APSO	1.158894	1.171444	1.166953	8.95×10^{-2}	13.1	0.16	0.1762	0.1672	8.48×10^{-2}
PPSO	1.157916	1.162164	1.159058	3.84×10^{-2}	13.17	0.1434	0.1495	0.1469	8.3×10^{-4}
LPPSO	1.149724	1.160641	1.154199	9.26×10^{-3}	13.79	0.1411	0.1485	0.1463	5.54×10^{-4}
ω_1= 0.5,ω_2= 0.5									
	Best	Worst	Mean	Std.	P_{SAVE}%	Best	Worst	Mean	Std.
FIPS	1.170601	1.188975	1.174615	5.73×10^{-1}	12.22	1.6078	1.9841	1.6681	1.25
FPSO	1.16699	1.178537	1.171857	2.74×10^{-2}	12.49	1.5868	1.7314	1.6006	4.38×10^{-2}
CLPSO	1.163697	1.1657	1.16512	1.48×10^{-3}	12.74	1.5901	1.727	1.6506	7.45×10^{-2}
APSO	1.166035	1.181395	1.171068	1.5×10^{-1}	12.56	1.548	1.6838	1.6293	5.78×10^{-2}
PPSO	1.164577	1.180617	1.168952	9.01×10^{-2}	12.67	1.4895	1.674	1.5835	2.59×10^{-2}
LPPSO	1.159578	1.166255	1.163422	9.93×10^{-4}	13.05	1.3728	1.4209	1.3992	8.18×10^{-3}

Table 7
Best control variables settings for active power loss minimization in IEEE 118-bus test system (p.u.).

Variable	KHA (Mukherjee and Mukherjee, 2016)	FF (Rajan and Malakar, 2015)	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PSOGSA (Radosavljević et al., 2016)	FAHCLPSO (Naderi et al., 2017)	GWO (Sulaiman et al., 2015)	PPSO	LPPSO
V_{G1}	1.0211	1.021665	0.9859	0.9875	1.0299	1.0120	1.0204	1.0048	1.0328
V_{G4}	1.0476	1.043732	1.0247	1.0286	1.0598	1.0523	1.0257	0.97657	1.0542
V_{G6}	1.0314	1.0334	1.0158	1.0111	1.0529	1.0666	1.0208	1.0197	1.0435
V_{G8}	1.1000	1.05013	1.0481	1.0101	0.9888	1.0597	1.0419	0.97929	1.0387
V_{G10}	1.1000	1.026539	1.0490	1.0015	0.9408	1.0725	1.0413	0.9987	1.0587
V_{G12}	1.0478	1.01976	1.0049	1.0133	1.0508	1.0333	1.0232	0.98632	1.0402
V_{G15}	1.0356	1.021911	0.9792	0.9922	1.0235	1.0012	1.0207	1.0046	1.0322
V_{G18}	1.0298	1.03564	0.9768	0.9948	1.0211	1.0058	1.0270	1.0119	1.0339
V_{G19}	1.0245	1.001754	0.9744	0.9868	1.0187	1.1000	1.0204	0.99967	1.0299
V_{G24}	1.0349	1.058576	1.0079	1.0025	1.0231	1.0971	1.0137	1.017	1.0445
V_{G25}	1.0787	1.081467	1.0396	1.0175	1.0281	1.0899	1.0270	1.0132	1.06
V_{G26}	1.0014	1.088557	1.06	1.0105	1.0599	1.1000	1.0386	0.97349	1.06
V_{G27}	1.0345	1.059599	0.9948	1.0442	1.0228	1.0654	1.0188	0.99074	1.0338
V_{G31}	1.0249	1.030586	0.9812	1.0185	1.0143	1.0318	1.0138	0.99454	1.029
V_{G32}	1.0349	1.051383	0.9903	1.0216	1.0194	1.0322	1.0135	1.0121	1.0328
V_{G34}	1.0749	0.985175	0.9823	0.9983	1.0207	0.9999	1.0261	0.9803	1.0404
V_{G36}	1.0749	1.043302	0.9754	0.9962	1.0183	0.9998	1.0261	0.99018	1.0368
V_{G40}	1.0245	1.009106	0.9685	1.0196	0.9935	1.0501	1.0125	1.008	1.0193
V_{G42}	1.0249	1.014088	0.9802	1.0093	0.9886	1.0231	1.0233	1.0211	1.0234
V_{G46}	1.0469	0.986644	1.0148	0.9892	1.0357	1.0005	1.0272	0.97835	1.0431
V_{G49}	1.0549	1.045022	1.0260	0.9976	1.0538	0.9897	1.0401	0.99223	1.057
V_{G54}	1.0457	1.044307	1.0044	0.9870	1.0436	0.9998	1.0230	0.99851	1.0367
V_{G55}	1.0274	0.999572	1.0010	0.9788	1.0404	1.0222	1.0221	1.014	1.0356
V_{G56}	1.0249	0.994247	1.0019	0.9811	1.0410	1.0008	1.0226	1.013	1.036
V_{G59}	1.0289	1.047607	1.0151	0.9974	1.0600	1.0731	1.0379	1.0204	1.0599
V_{G61}	1.0789	1.030507	1.0075	0.9888	1.0600	1.0258	1.0241	1.0033	1.06
V_{G62}	1.0659	1.03358	1.0005	0.9785	1.0566	1.0059	1.0199	1.0017	1.0563
V_{G65}	1.0991	1.06538	1.0110	1.0271	1.0239	1.0630	1.0465	1.0005	1.06
V_{G66}	1.0451	1.028989	1.0277	0.9932	1.0600	1.0312	1.0378	0.98763	1.06
V_{G69}	1.0359	1.046139	1.0328	1.0308	1.0600	1.0636	1.0501	0.9826	1.06
V_{G70}	1.0542	1.07727	0.983	0.9981	1.0350	1.1000	1.0243	0.96987	1.0367
V_{G72}	1.0511	1.022816	0.988	1.0086	1.0302	1.0500	1.0187	0.98338	1.0379
V_{G73}	1.0459	1.031771	0.98427	1.0014	1.0587	1.0981	1.0397	0.9787	1.0358
V_{G74}	1.0359	1.030611	0.9578	0.9695	1.0066	1.0444	1.0170	0.98634	1.0272
V_{G76}	1.0259	1.015462	0.9469	0.9521	0.9957	1.0037	1.0080	1.0095	1.0249
V_{G77}	1.0280	1.051973	0.9900	0.9950	1.0382	1.0559	1.0192	1.0107	1.0468
V_{G80}	1.0421	1.039807	1.0078	1.0147	1.0542	0.9999	1.0329	0.99454	1.06
V_{G85}	1.0353	1.077938	0.9963	0.9986	1.0446	1.0882	1.0224	0.99397	1.06
V_{G87}	1.0963	1.002763	0.9991	0.9908	1.0515	1.0303	1.0361	1.0254	1.06
V_{G89}	1.0759	1.074747	1.02271	1.0231	1.0600	1.0001	1.0558	1.0046	1.06
V_{G90}	1.0425	1.047818	0.9994	0.9917	1.0323	1.0018	1.029	0.9897	1.0414
V_{G91}	1.0358	1.048983	0.9969	0.9967	1.0273	1.0298	1.0127	1.0104	1.0449
V_{G92}	1.0516	1.047601	0.9962	1.002	1.0431	1.1005	1.036	0.98434	1.0561
V_{G99}	1.0415	1.042693	0.9783	0.9951	1.0072	1.0498	1.0297	1.0193	1.0449
V_{G100}	1.0426	1.038511	0.9795	1.0089	1.0522	1.0565	1.036	1.0039	1.0446
V_{G103}	1.0220	1.022228	0.9599	0.9999	1.0480	1.0413	1.0232	1.0054	1.0353
V_{G104}	1.0041	1.03061	0.94	0.9874	1.0353	1.0189	1.018	1.0234	1.0163
V_{G105}	1.0147	1.053364	0.9447	0.9864	1.0339	1.1000	1.0176	0.99694	1.0105
V_{G107}	0.9879	1.014579	0.9531	1.0014	1.0422	1.0222	1.0201	1.014	0.9974
V_{G110}	1.0120	1.034131	0.9732	0.9896	1.0196	1.0115	1.0207	0.98627	1.008
V_{G111}	1.0258	1.031144	1.0212	1.0178	1.0270	1.1000	1.0261	0.96426	1.0164
V_{G112}	0.9928	1.011916	0.9546	0.9744	1.0015	1.0500	1.0066	0.98486	0.992
V_{G113}	1.0415	1.021931	0.9820	1.0131	1.0337	1.0099	1.0251	1.0009	1.043
V_{G116}	1.0254	1.053512	0.9845	1.0163	1.0067	1.0500	1.0342	0.99395	1.06
$T_{5\text{–}8}$	1.0740	1.002155	1.0137	0.9619	0.9182	1.0214	1.0208	1.02394	0.98
$T_{25\text{–}26}$	1.0245	0.941079	1.0628	0.9961	1.1000	1.0533	1.0279	0.986514	1.1
$T_{17\text{–}30}$	1.0456	0.974903	1.02714	0.9791	0.9790	1.0555	1.0323	0.98321	0.99
$T_{37\text{–}38}$	0.9874	0.989385	1.0021	1.0216	0.9759	0.9995	1.0209	1.01461	1.0
$T_{59\text{–}63}$	1.0389	0.992515	0.9664	0.9906	0.9000	1.0619	1.0091	0.972579	0.98
$T_{61\text{–}64}$	1.0147	0.98305	1.0014	1.0313	0.9287	1.0318	1.0366	0.996988	1.0
$T_{65\text{–}66}$	0.9245	0.971375	1.0304	1.0435	1.0057	1.0490	1.0301	1.00024	0.9
$T_{68\text{–}69}$	0.9945	0.936734	0.9018	0.9976	0.9715	0.9660	1.0234	1.00105	0.96
$T_{80\text{–}81}$	1.0780	0.979664	0.9411	0.9400	0.9459	0.9732	1.0211	1.01327	0.98
Q_{C5} (p.u.)	0.3979	0.0	0.1	0.018675	−0.335074	0.003500	−0.3976	−0.16904	−0.0837
Q_{C34} (p.u.)	0.0005	0.02389537	0.0132	0.035622	0.076243	0.101922	0.1379	0.053699	0.0343
Q_{C37} (p.u.)	0.2389	0.0	0.0	0.060115	−0.197317	0.017500	−0.2473	−0.17276	−0.0822
Q_{C44} (p.u.)	0.0009	0.06471033	0.0930	0.060068	0.065258	0.044000	0.099571	0.05101	0.0381

(continued on next page)

Table 7 (*continued*)

Variable	KHA (Mukherjee and Mukherjee, 2016)	FF (Rajan and Malakar, 2015)	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PSOGSA (Radosavljević et al., 2016)	FAHCLPSO (Naderi et al., 2017)	GWO (Sulaiman et al., 2015)	PPSO	LPPSO
Q_{C45} (p. u.)	0.0489	0.05015351	0.0886	0.052212	0.045300	0.069894	0.098678	0.04417	0.0109
Q_{C46} (p. u.)	0.0002	0.01108324	0.0334	0.044975	0.031784	0.071289	0.099186	0.044444	0.0
Q_{C48} (p. u.)	0.0005	0.06989812	0.0	0.039845	0.118388	0.066668	0.1489	0.100141	0.0339
Q_{C74} (p. u.)	0.0003	0.07310902	0.0390	0.068448	0.038061	0.110952	0.11972	0.007024	0.0
Q_{C79} (p. u.)	0.0008	0.09132848	0.0630	0.053023	0.139863	0.150000	0.19649	0.125731	0.0
Q_{C82} (p. u.)	0.0419	0.09882076	0.0758	0.050808	0.177504	0.105509	0.1989	0.099487	0.0
Q_{C83} (p. u.)	0.0500	0.06716357	0.0227	0.052515	0.019938	0.55540	0.099515	0.022175	0.0
Q_{C105} (p. u.)	0.0010	0.1066619	0.0	0.040520	0.068200	0.151895	0.19968	0.128145	0.2
Q_{C107} (p. u.)	0.0076	0.04262622	0.0	0.058284	0.060000	0.044140	0.059136	0.031749	0.0067
Q_{C110} (p. u.)	0.0222	0.02402687	0.0112	0.037223	0.044194	0.022310	0.058834	0.043105	0.0289
Ploss (p. u.)	1.1885	1.3542	1.286945	1.304973	1.224709	1.162479	1.2065	1.2407	1.149724

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i = 1, \ldots, NPQ \tag{13}$$

$$S_{li} \le S_{li}^{\max}, \quad i = 1, \ldots, NTL \tag{14}$$

where $V_{Li}^{\min}$ and $V_{Li}^{\max}$ are limits of load voltage of ith bus, and S_{li} and $S_{li}^{\max}$ are apparent power flow of ith branch and its maximum limit, respectively.

2.4. Multi-objective conversion for ORPD

In a multi-objective ORPD problem, the ranges of different objective function values are not the same. So, these functions must be normalized to have the same ranges. Afterward, the normalized values of objective functions can be combined in order to evaluate the solutions. The function that is used for normalizing each of the sub-objectives to range (0, 1), can be described as follows:

$$f_{Ji}(x,u) = \begin{cases} 0 & for\, J_i(x,u) \le J_i^{\min} \\ 1 & for\, J_i(x,u) \ge J_i^{\max} \\ \dfrac{J_i^{\max} - J_i(x,u)}{J_i^{\max} - J_i^{\min}} & for\, J_i^{\min} \le J_i(x,u) \le J_i^{\max} \end{cases} \tag{15}$$

Where $J_i^{\min}$ and $J_i^{\max}$ are the minimum and maximum values of $f_{Ji}(x,u)$ function, respectively, which must be achieved by optimizing the objective function in a single objective mode.

The control variables are self-constrained, and state variables are constrained using penalty terms. So, the objective function can be stated as follows (Iba, 1994; Devaraj & Roselyn, 2010):

$$\min f = \omega_1 f_1 + \omega_2 f_2 + \lambda_V \sum_{i \in N_V^{\lim}} \left(V_i - V_i^{\lim}\right)^2 + \lambda_Q \sum_{i \in N_Q^{\lim}} \left(Q_{Gi} - Q_{Gi}^{\lim}\right)^2 \tag{16}$$

where ω_i (i = 1, 2) are the user-defined constants used to weigh the importance of each sub-objective in the optimization process; λ_V and λ_Q are the penalty factors, $N_V^{\lim}$ indicates the buses whose voltage magnitude limits are violated, $N_V^{\lim}$ is indicates the generator whose reactive power injections are out of permissible range, and $V_i^{\lim}$ and $Q_{Gi}^{\lim}$ are defined as follows (Badar et al., 2012):

$$V_i^{\lim} = \begin{cases} V_i & if\ V_i^{\min} \le V_i \le V_i^{\max} \\ V_i^{\min}, & if\ V_i < V_i^{\min} \\ V_i^{max}, & if\ V_i > V_i^{\max} \end{cases} \tag{17}$$

$$Q_{Gi}^{\lim} = \begin{cases} Q_{Gi}, & if\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \\ Q_{Gi}^{\min}, & if\ Q_{Gi} < Q_{Gi}^{\min} \\ Q_{Gi}^{\max}, & if\ Q_{Gi} > Q_{Gi}^{\max} \end{cases} \tag{18}$$

3. PSO, PPSO, and the proposed LPPSO algorithm

3.1. The basic PSO algorithm

The basic PSO starts with randomly creating the initial swarm, comprising the initial solutions, and their velocities. Then, the particles' positions are updated through the iterations using as follows:

$$V_{id}^{t+1} = V_{id}^{t} + c_1 \times r1_{id} \times \left(\mathrm{PB}_{id}^{t} - x_{id}^{t}\right) + c_2 \times r2_{id} \times \left(\mathrm{GB}_{d}^{t} - x_{id}^{t}\right) \tag{19}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{20}$$

Where i, t, and d are the indices for particles, iterations, and dimensions, respectively, X_i and V_i are the position and velocity vectors, respectively, $\mathrm{PB_i}$ is the personal best position of the ith particle, GB is the global best partition of the whole swarm, c_1 and c_2 are two constant parameters, and $r1_{id}$ and $r2_{id}$ are two uniformly distributed random numbers.

These position and velocity vectors are randomly initiated at the beginning of the optimization process. Then, they are updated using (19) and (20) through the optimization process.

The particles' velocities are bounded as $-V_{max} \le V_i \le V_{max}$ to reduce the probability of moving out of the feasible decision region.

3.2. Phasor particle swarm optimization (PPSO)

In PPSO, the control parameters of the particle swarm optimization are replaced using suitable functions of phase angles θ, to help the algorithm experience optimizing behaviors by assigning different values to control parameters through iterations (Ghasemi et al., 2019). The phase angle of each particle is a scalar number, and in PPSO each particle has a magnitude vector and a phase angle. The equation for

Table 8
Best control variables settings for voltage deviation minimization in IEEE 118-bus test system (p.u.).

Variable	FAHCLPSO (Naderi et al., 2017)	FF (Rajan and Malakar, 2015)	KHA (Mukherjee and Mukherjee, 2016)	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PSOGSA (Radosavljević et al., 2016)	PPSO	LPPSO
V_{G1}	1.0310	1.00463	1.0041	0.9907	0.9785	0.9809	1.0148	1.0036
V_{G4}	1.0429	1.00322	1.0049	1.0387	1.0234	1.0127	0.9647	1.0097
V_{G6}	1.0181	1.01005	0.9989	1.0114	0.9983	0.9976	0.98155	0.9946
V_{G8}	1.0731	0.96686	0.9975	0.978	1.0073	1.0091	0.98684	0.9915
V_{G10}	1.0912	0.96716	1.0145	1.0086	0.9896	0.9731	1.0112	0.991
V_{G12}	1.0443	0.99459	1.0147	1.0131	1.0050	1.0057	0.99527	1.0106
V_{G15}	1.0198	1.01386	1.0142	1.006	0.9850	1.0011	0.97711	1.0027
V_{G18}	1.0550	1.04122	1.0061	1.0104	0.9911	1.0002	1.0011	0.9813
V_{G19}	1.0905	1.01864	1.0439	1.004	0.9862	0.9975	0.99238	1.0336
V_{G24}	1.0798	1.02281	0.9965	1.027	1.0085	1.0240	0.97079	1.0048
V_{G25}	1.0636	0.99266	0.9948	1.0505	1.0067	1.0445	1.0118	0.9938
V_{G26}	1.1000	1.05527	1.0120	1.0299	0.9944	1.0600	0.98888	0.9861
V_{G27}	1.0218	1.00899	1.0105	1.0064	1.0052	0.9765	1.0201	1.0076
V_{G31}	1.0789	0.99973	1.0047	1.00115	0.9939	1.0089	0.99707	1.0028
V_{G32}	1.0505	0.99075	1.0142	1.0015	1.0029	0.9944	1.0236	1.0027
V_{G34}	1.0420	0.98638	1.0157	1.014	1.0198	1.0072	0.98768	1.0124
V_{G36}	1.0099	0.99890	0.9991	1.0071	1.0164	1.0050	1.0151	0.9982
V_{G40}	1.0834	1.00631	1.0014	0.9994	0.9773	0.9881	0.98917	1.0031
V_{G42}	1.0917	1.00278	1.0369	1.0255	0.9776	1.0581	0.97314	1.0179
V_{G46}	0.9999	0.97417	1.0753	1.0536	0.9982	0.9987	0.98772	1.0236
V_{G49}	1.0088	0.96895	1.0142	1.0149	0.9935	1.0150	1.031	1.004
V_{G54}	1.0009	1.02491	1.0111	1.0463	0.9945	1.0467	1.0144	1.0249
V_{G55}	1.0414	1.00222	0.9714	1.0397	0.99	1.0412	0.97786	1.028
V_{G56}	1.0055	0.98991	1.0214	1.0407	0.9901	1.0409	0.99549	1.0146
V_{G59}	1.0639	0.98646	0.9649	1.06	1.0086	1.0600	1.0088	1.0353
V_{G61}	1.0193	1.00483	1.0240	0.9871	1.0030	0.9753	0.99933	0.9927
V_{G62}	1.0123	1.00713	0.9914	0.9856	0.9961	0.9792	0.97747	1.0259
V_{G65}	1.0719	0.97381	1.0542	1.0348	1.0265	0.9938	0.95466	0.9923
V_{G66}	1.0818	0.97196	1.0364	1.0208	1.0129	1.0463	0.97445	0.9901
V_{G69}	1.0450	0.99260	0.9752	1.06	1.06	1.0336	1.0006	0.9679
V_{G70}	1.0890	1.04687	1.0269	0.9996	1.0043	1.0000	1.0278	1.0333
V_{G72}	1.0500	0.96503	1.0258	0.9420	0.9733	0.9546	0.99595	1.06
V_{G73}	1.0360	0.99666	0.9981	1.005	1.003	1.0101	1.0027	0.9415
V_{G74}	1.0128	1.04279	1.0249	0.9671	0.9777	0.9749	1.0045	1.0113
V_{G76}	1.0085	1.06470	1.0245	0.955	0.9631	0.9633	1.0264	1.0132
V_{G77}	1.0888	1.00048	1.0259	0.9992	1.0033	1.0189	1.005	1.0072
V_{G80}	1.0111	1.01954	1.0259	1.0156	1.0201	1.0498	1.0065	1.0166
V_{G85}	0.9789	1.029202	1.0298	1.0131	0.9985	1.0080	0.99725	1.0113
V_{G87}	0.9955	0.996874	1.0459	1.0034	1.0324	1.0112	0.97689	1.0056
V_{G89}	1.0452	1.02193	1.0145	1.06	1.0174	1.0234	1.0007	1.0078
V_{G90}	1.0215	1.01266	1.0279	0.9774	1.0022	1.0550	0.97908	1.06
V_{G91}	1.0719	1.02138	1.0459	0.9954	1.0277	1.0284	1.029	0.94
V_{G92}	1.1000	1.00899	1.0145	1.0291	1.0074	1.0066	1.0141	1.0131
V_{G99}	1.0465	1.00278	1.0259	0.977	0.9782	0.9417	0.98207	1.0347
V_{G100}	1.0333	0.98207	1.0245	1.0339	1.0188	0.9906	1.0042	1.0177
V_{G103}	1.0458	1.05036	1.0245	1.0297	1.0094	0.9778	0.99704	1.0235
V_{G104}	1.0127	1.01701	1.0458	1.0147	0.9959	0.9741	0.98256	1.06
V_{G105}	1.0450	0.99261	1.0214	1.0194	0.9951	0.9865	0.97903	1.0004
V_{G107}	1.0515	1.01568	0.9974	1.0517	1.016	1.0600	0.96348	1.0314
V_{G110}	1.0121	1.02782	0.9948	1.0345	1.0149	0.9892	1.0014	1.004
V_{G111}	1.1000	1.02538	1.0459	1.0492	1.0372	1.0595	1.0203	1.0067
V_{G112}	1.0497	1.01059	1.0247	1.0494	1.0164	0.9405	1.0004	0.9848
V_{G113}	1.0111	0.99522	0.9987	1.0272	1.0130	0.9937	0.98602	0.9935
V_{G116}	1.0418	0.99820	0.9966	0.991899	0.985321	1.0087	1.0127	1.0065
T_{5-8}	1.0763	0.97976	1.0245	0.9991	1.0511	0.9994	1.04337	1.04
T_{25-26}	1.0339	1.02312	0.9958	1.0145	1.0100	1.0567	1.03704	1.0
T_{17-30}	1.0812	0.95113	0.9990	0.9697	1.008	0.9024	0.992757	1.0
T_{37-38}	0.9985	0.96452	0.9851	0.9669	0.928	0.9604	1.00704	0.98
T_{59-63}	1.0435	1.00350	1.0514	0.9127	1.0383	0.9116	0.979825	0.97
T_{61-64}	1.0512	0.99719	0.9459	1.0493	1.0909	1.0539	1.06051	1.01
T_{65-66}	1.0340	1.00425	0.9759	1.0383	1.0068	0.9000	0.995074	1.1
T_{68-69}	0.9797	0.95071	1.0230	0.9261	0.9566	0.9000	0.990573	0.96
T_{80-81}	0.9800	0.96888	0.9725	0.9784	0.9686	0.9376	1.02189	0.97
Q_{C5} (p.u.)	0.015000	0.0	0.2815	0.1	0.083649	−0.273957	−0.14376	−0.0329
Q_{C34} (p.u.)	0.128756	0.0746849	0.0359	0.0268	0.066130	0.070607	0.095218	0.1313
Q_{C37} (p.u.)	0.043150	0.0	0.0942	0.0528	0.073458	−0.106680	−0.11822	−0.1017
Q_{C44} (p.u.)	0.049981	0.0586649	0.0425	0.0370	0.011125	0.039224	0.039109	0.0
Q_{C45} (p.u.)	0.081112	0.0479066	0.0346	0.0900	0.05294	0.054634	0.049764	0.0

(continued on next page)

Table 8 (*continued*)

Variable	FAHCLPSO (Naderi et al., 2017)	FF (Rajan and Malakar, 2015)	KHA (Mukherjee and Mukherjee, 2016)	ICA (Mehdinejad et al., 2016)	PSO (Mehdinejad et al., 2016)	PSOGSA (Radosavljević et al., 2016)	PPSO	LPPSO
Q_{C46} (p. u.)	0.100292	0.0579231	0.0045	0.0245	0.081801	0.092847	0.077423	0.0435
Q_{C48} (p. u.)	0.055000	0.0599441	0.1214	0.0093	0.08236	0.0	0.06637	0.15
Q_{C74} (p. u.)	0.108156	0.0426537	0.0212	0.1	0.037390	0.024011	0.085006	0.0904
Q_{C79} (p. u.)	0.150000	0.094375	0.0863	0.1	0.061524	0.150490	0.076932	0.2
Q_{C82} (p. u.)	0.098256	0.08075733	0.0942	0.0462	0.07674	0.104150	0.122099	0.0
Q_{C83} (p. u.)	0.050000	0.03870194	0.0426	0.0601	0.073022	0.000106	0.034425	0.0
Q_{C105} (p. u.)	0.181298	0.09932968	0.2469	0.0728	0.052062	0.019242	0.032444	0.0002
Q_{C107} (p. u.)	0.050055	0.04053948	0.0089	0.0292	0.014605	0.040001	0.030154	0.0194
Q_{C110} (p. u.)	0.044497	0.03346277	0.0412	0.0702	0.00805	0.010668	0.032747	0.0319
VD	0.2218	0.378	0.2558	0.6789	0.7711	0.7308	0.2169	**0.1411**

Table 9
Statistical details for active power loss minimization in IEEE 118-bus power system.

Algorithms	Mean (p.u.)	Worst (p.u.)	Best (p.u.)	Time (*sec*)	%Psave	Std. (p.u.)
CFA (Ghasemi et al., 2022)	1.159865	1.163178	1.154597	65.19	–	1.28e-03
CS (Ghasemi et al., 2022)	1.24088	1.288526	1.186402	537.66	–	1.619e-03
ABC (Ghasemi et al., 2022)	1.222755	1.266823	1.192148	510.45	–	2.063e-03
DE/best/1 (Ghasemi et al., 2022)	1.192183	1.217954	1.173356	515.74	–	2.487e-03
Improved PSO (Ghasemi et al., 2022)	1.199905	1.237531	1.183369	551.95	–	3.786e-03
ABC (Shaheen et al., 2021)	–	–	1.3699	–	–	–
HHO (Shaheen et al., 2021)	–	–	1.320394	–	–	–
PSOGWO (Shaheen et al., 2021)	–	–	1.318458	–	–	–
SMA (Wei et al., 2021)	1.180399	1.188109	1.166795	112.8062	–	0.5734e-03
MVO (Wei et al., 2021)	1.299273	1.311348	1.285667	105.3629	–	0.6721e-03
PFA (Wei et al., 2021)	1.179972	1.198574	1.165439	124.5478	–	0.9542e-03
PPSO	1.33852	1.45476	1.24072	220.14	0.0696	5.49−2
LPPSO	1.154199	1.160641	1.149724	225.06	13.79	9.26e−3

Table 10
Statistical details for voltage deviation minimization in IEEE 118-bus power system.

Algorithms	Mean (p.u.)	Worst (p.u.)	Best (p. u.)	Times (*sec*)	Std.
NGBWCA (Heidari et al., 2017)	–	–	0.3194	–	–
WCA (Heidari et al., 2017)	–	–	0.3752	–	–
OGSA (Heidari et al., 2017)	–	–	0.3666	–	–
CBA-IV (Mugemanyi et al., 2020)	0.3036	0.3041	0.3032		3.06e−4
CBA-III (Mugemanyi et al., 2020)	0.3062	0.0372	0.3059		3.23e−4
CBA (Mugemanyi et al., 2020)	0.3187	0.3206	0.3172		9.75e−4
ALC-PSO (Singh et al., 2015)	0.3281	0.3743	0.3262		9.5e−5
PPSO	0.2918	0.3652	0.2169	254.78	1.08e−3
LPPSO	0.1463	0.1485	0.1411	263.14	5.54e−4

calculating the velocity of the particles in PPSO is as follows:

$$V_i^t = \left|\cos\theta_i^t\right|^{2*\sin\theta_i^t} \times \left(\mathrm{PB}_i^t - X_i^t\right) + \left|\sin\theta_i^t\right|^{2*\cos\theta_i^t} \times \left(\mathrm{GB}^t - X_i^t\right) \tag{21}$$

Furthermore, the phase angle and maximum velocities are updated using the following equations:

$$\theta_i^{t+1} = \theta_i^t + \left|\cos\left(\theta_i^t\right) + \sin\left(\theta_i^t\right)\right| \times (2\pi) \tag{22}$$

$$V_{i,\max}^t = \left|\cos\theta_i^t\right|^2 \times \left(X_{\max} - X_{\min}\right) \tag{23}$$

3.3. The proposed LPPSO algorithm

In this paper, a new combined algorithm based on the Phasor and Lévy-flight particle swarm optimization algorithm (LPPSO) is proposed in order to improve the particle swarm optimization and increase the diversity and adaptability of the algorithm. The equation for calculating the velocity of the particles in LPPSO is as follows:

$$V_i^t = \left|\cos\theta_i^t\right|^{2*\sin\theta_i^t} \times \left(\mathrm{PB}_i^t - X_i^t\right) + \left|\sin\theta_i^t\right|^{2*\cos\theta_i^t} \times \left(\mathrm{GB}^t - X_i^t\right) + \alpha \mathrm{sign}\left[\mathrm{rand} - \frac{1}{2}\right] \odot \mathrm{Levy} \tag{24}$$

The third term of the above equation is used for randomizing the velocities through Lévy flights, where α is the randomization parameter. The term $\odot$ refers to entry-wise multiplication. The expressionsign$\left[\mathrm{rand} - \frac{1}{2}\right]$, where rand is a uniform random number in the range [0, (Siyuan & Suwen, 2017)], provides a random direction or sign, and the randomized step length is taken from a Lévy distribution.

$$\mathrm{Levy} \sim u = t^{-\lambda}, (1 < \lambda \leq 3), \tag{25}$$

It is boundless in variance and infinite in mean. For the optimization situations discussed in this article, we can use $\alpha \in$ [0, (Siyuan & Suwen,

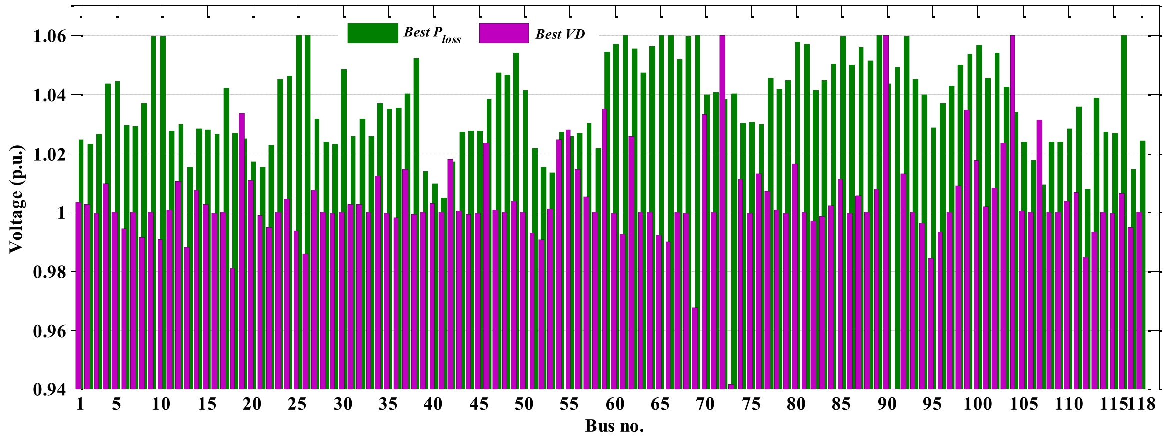

Fig. 7. Voltage profiles of the best solutions for IEEE 118-bus power system.

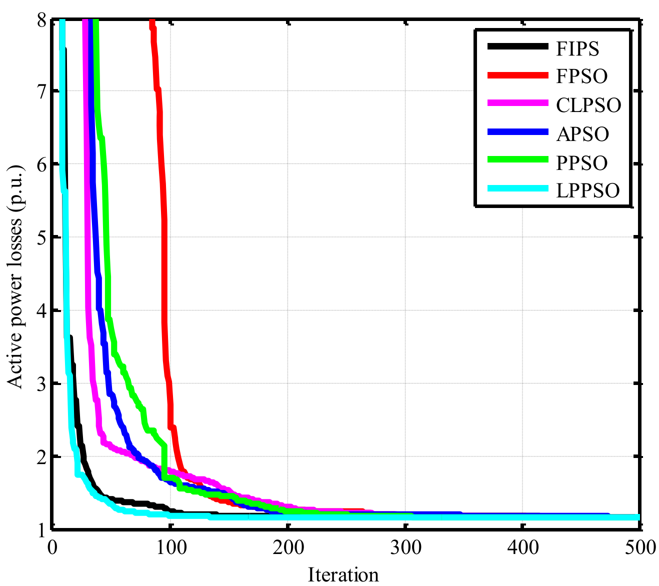

Fig. 8. Convergence characteristics of different PSO algorithms for active power loss minimization in IEEE 118-bus power system.

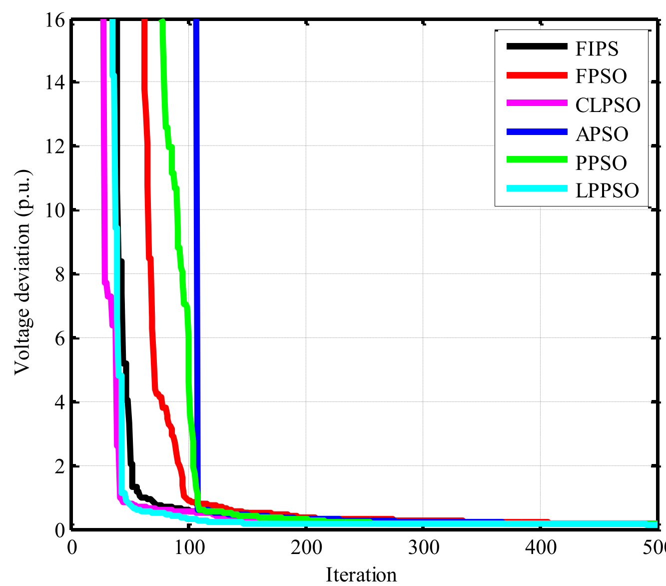

Fig. 9. Convergence characteristics of different PSO algorithms for voltage deviation minimization in IEEE 118-bus power system.

2017)] and $\lambda = 1.5$. Fig. 1 shows the flowchart of the LPPSO algorithm.

4. Simulation results of solving ORPD using LPPSO

In order to verify the efficiency of the LPPSO in solving ORPD problems, the objective of the ORPD problem is selected as minimizing the real power losses and bus voltage deviation in the network while satisfying the operational constraints. IEEE 57-bus and IEEE 118-bus power test systems are used for the study. For the IEEE 57-bus power system, the maximum iterations and maximum population size for all PSO algorithms were set to 250 and 50, respectively. This resulted in a total number of function evaluations (NFE) equal to 12,500 for all algorithms. Similarly, for the IEEE 118-bus power test system, the maximum iterations and maximum population size for all PSO algorithms were set to 500 and 100, respectively. This led to a total number of function evaluations (NFE) equal to 50,000 for all algorithms. The performance of LPPSO in solving ORPD problem was compared with that of other variants of PSO including adaptive PSO (APSO) (Zhan & Zhang, 2008), comprehensive learning PSO (CLPSO) (Liang et al., 2006), fully informed particle swarm (FIPS) (Mendes et al., 2004), Frankenstein's PSO (FPSO) (Montes de Oca et al., 2009), and PPSO (Ghasemi et al., 2019).

The reactive power outputs of shunt compensators and the tap settings of transformers are discrete variables whose step sizes are 0.01 p.u., and $\lambda_V$and λ_Q in (16) are set to 500 (Ghasemi et al., 2014; Devaraj & Roselyn, 2010). The simulation results show the best solutions through 30 independent runs.

4.1. IEEE 57-bus test system

One-line diagram of the standard IEEE 57-bus test power system is presented in Fig. 2. This test system includes seven generating units at the buses 1(G_1), 2 (G_2), 3 (G_3), 6 (G_6), 8 (G_8), 9 (G_9), and 12 (G_{12}); 80 transmission lines and 15 lines equipped with tap changing transformers. The shunt VAR compensators are located on buses 18 (Q_{C18}), 25 (Q_{C25}), and 53 (Q_{C53}). The data of buses and branches, and the minimum and maximum real power generations of generators are selected as in Devaraj and Roselyn (2010). The limits of all control variables were extracted from Ghasemi (2017).

The optimal reactive power dispatch (ORPD) results for the IEEE 57-bus test system found by 30 independent runs of different PSO variants are presented in Table 1, including statistical performance indices like mean (the mean of power losses and voltage deviation), worst (the worst of power losses and voltage deviation), best (the best of power losses and voltage deviation), std (the standard deviation), and$\%P_{SAVE}$ (the saving percent of the active power losses). The optimal results obtained using the proposed LPPSO method are compared with the results of other improved PSO variants. From the simulation results, it is obvious that the proposed LPPSO algorithm outperforms other improved PSO algorithms in solving reactive power and voltage optimal control problems. It can be observed in Table 1 that a 14.2 % reduction in power losses is achieved in the 57-bus test system using the proposed LPPSO method, which is more than that obtained by the other improved PSO algorithms. The best result for voltage deviation of all improved PSO algorithms is 0.7285 p.u. which is achieved by the proposed LPPSO method. This proves the effectiveness of the LPPSO algorithm in solving reactive power and voltage optimal control problems. It is obvious that the optimized real power losses (and voltage deviation) are greatly affected by the increase/reduction of values of ω_1 and ω_2. Tables 2 and 3 illustrate the optimal setting of control variables and their corresponding objective values obtained by proposed algorithms for active power losses minimization (ω_1 =1, ω_2 =0) and the best solution for voltage deviation minimization (ω_1 =0, ω_2 =1), respectively. Statistical details for active power loss minimization and voltage deviation minimization in IEEE 57-bus power system is presented in Tables 4 and 5, respectively. It is seen from these tables that regarding the Best index, LPPSO outperforms all other algorithms in both cases, and for the Mean index, it outperforms all other algorithms in both cases, except for SALTLBO (Alghamdi, 2022) which gives a better Mean index in voltage deviation minimization case. The results prove the effectiveness of the proposed LPPSO algorithm in solving the ORPD problem.

The system voltage profile of the best solution of the voltage deviation minimization (by LPPSO algorithm) is compared to that of the best solution of active power losses minimization (by LPPSO algorithm) as shown in Fig. 3. It is obvious that the voltage profile for the best solution of voltage deviation minimization is superior to that of the best solution of active power losses minimization. Furthermore, it is seen from Fig. 3 that the voltage magnitudes of the system buses for the solutions found by LPPSO for both cases are within their permissible range.

Convergence characteristics of different PSO algorithms for active power loss minimization and voltage deviation minimization in IEEE 57-bus power system are shown in Figs. 4 and 5, respectively. It is obvious from these figures that LPPSO gives acceptable convergence characteristics for both cases. It should be noted that, since a constant population size of 50 was used for all PSO algorithms in the 57-bus system, each iteration of the algorithms corresponds to 50 function evaluations.

4.2. IEEE 118-bus test system

For the sake of evaluating the performance and efficiency of LPPSO in solving large-scale reactive power optimal control problems, the PSO algorithms are also used to solve ORPD in IEEE large-scale 118-bus test power system. The one-line diagram of this test system is displayed in Fig. 6. The limits for the control variables were extracted from Ghasemi (2017). This system includes 54 generators, 14 shunt VAR compensators, and nine tap-changing transformers (Devaraj & Roselyn, 2010).

The best solutions of ORPD found by PSO algorithms in 30 runs are covered in Table 6. It is deduced from this table that applying the LPPSO algorithm has caused an active power loss reduction of 13.79 %, which is more than the reduction of power loss achieved by all other algorithms. Furthermore, the least voltage deviation is 0.1411 p.u. which is also achieved by the LPPSO method. Judging from the results presented in Table 6, it can be deduced that the proposed LPPSO algorithm outperforms all other PSO algorithms. The values of the control variables for this large-scale test power system are not presented because of space limitations. The best solution found by the PSO algorithms over 30 runs for power loss minimization and voltage deviation minimization are tabulated in Tables 7 and 8, respectively. Statistical details for active power loss minimization and voltage deviation minimization in IEEE 118-bus power system is presented in Tables 9 and 10, respectively. It is seen from these tables that LPPSO outperforms all other algorithms in both cases for both the Best and the Mean index. The results prove the effectiveness of the proposed LPPSO algorithm in solving the ORPD problem.

The large-scale system voltage profile of the best solution of the voltage deviation minimization (by LPPSO algorithm) is compared to that of the best solution of active power losses minimization (by LPPSO algorithm) as presented in Fig. 7. It is clear that the voltage profile for the best solution of voltage deviation minimization is superior to that of the best solution of active power losses minimization. Furthermore, it is seen from Fig. 7 that the voltage magnitudes of the system buses for the solutions found by LPPSO for both cases are within their permissible range.

Convergence characteristics of different PSO algorithms for active power loss minimization and voltage deviation minimization in IEEE 118-bus power system are shown in Figs. 8 and 9, respectively. It can be seen from these figures that LPPSO demonstrates satisfactory convergence characteristics for both cases. It is worth mentioning that, due to a fixed population size of 100 applied to all PSO algorithms in the 118-bus system, each iteration of the algorithms results in 100 function evaluations.

5. Conclusion

A new and efficient particle swarm optimization (PSO) algorithm was successfully applied to solve reactive power optimal control (ORPD) problems to minimize the active power losses and bus voltage deviation. The proposed Lévy-flight phasor particle swarm optimization (LPPSO) algorithm is effective for solving ORPD problems while considering real power losses and voltage profile in two standard large-scale power systems and outperforms several studied PSO algorithms in this study including FIPS, FPSO, CLPSO, APSO, and original PPSO algorithm in solving this problem. Furthermore, it was shown that the proposed LPPSO algorithm outperforms the several state-of-the-art algorithms in solving reactive power optimal control problems in large-scale power systems.

CRediT authorship contribution statement

Milad Gil: Conceptualization, Software, Writing – original draft. **Ebrahim Akbari:** Writing – original draft, Methodology. **Abolfazl Rahimnejad:** Writing – review & editing, Resources. **Mojtaba Ghasemi:** Visualization, Validation. **S. Andrew Gadsden:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.iswa.2024.200398.

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