Improved social spider optimization algorithm for optimal reactive power dispatch problem with different objectives

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Abstract

This paper proposes an improved social spider optimization (ISSO) for achieving different objectives of optimal reactive power dispatch (ORPD). The proposed ISSO method is developed by applying two modifications on new solution generation process. The proposed method uses only one modified equation for producing the first new solution generation and the second new solution generation while the standard SSO uses two equations for each process. The improvement in the proposed method is confirmed by solving benchmark optimization functions, IEEE 30-bus system and IEEE 118-bus system. Obtained results from ISSO are compared to those from other existing methods available in other studies together with other popular and state-of-the-art methods, which are implemented in the work. As compared to standard SSO for application to ORPD problem, ISSO can reduce the number of computation steps and one control parameter, and shorten simulation time. About the result comparisons with SSO and other remaining methods, ISSO can find more favorable solutions with higher quality and ISSO can stabilize solution search function with approximately all trial runs finding lower value of fitness. Furthermore, the strong search ability of ISSO is also indicated because it uses less value for control parameters. As a result, the proposed ISSO method can be a very effective optimization tool for dealing with the ORPD problem.

List of symbols

HI	The highest iteration
N_{bus}	Number of buses in the considered power system
N_c	Number of VAR compensator buses
N_{fs}, N_{ms}	Number of females and males, respectively
N_G	Number of generator buses
N_{line}	Number of transmission lines
N_{load}	Number of load buses in the considered power system
N_{pop}	Population size or the sum of males and females
N_t	Number of buses with transformer
P_{di}, Q_{di}	Real and reactive power required by load of bus i
P_m	Movement probability of female spiders
Q_{ci}	Reactive power generation of VAR compensator of bus i
$Q_{ci,min}$, $Q_{ci,max}$	Lower and upper limitations of reactive power generation of VAR compensator at bus i
$Q_{Gi,min}$, $Q_{Gi,max}$	Lower and upper limitations of reactive power generation of generator at bus i, respectively
RN_f	Random number within 0 and 1 for female spider f
$S_{l,max}$	Maximum apparent power flow of line l
$T_{i,min}$, $T_{i,max}$	Lower and upper limitations of tap changer of transformer at bus i

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$V_{Gi,\min}$, $V_{Gi,\max}$	Lower and upper limitations of voltage magnitude of generator at bus i, respectively
V_i, V_j	Voltage magnitude of buses i and j
$V_{\text{load}i,\min}$, $V_{\text{load}i,\max}$	Lower and upper limitations of voltage magnitude of the load at bus i, respectively
$X_{\text{fs},f}$	Position of female spider f corresponding to a solution
X_{Gbest}	Position of the best spider corresponding to the best solution
$X_{\text{ms},m}$	Position of male spider m corresponding to a solution

Abbreviation

ABCA	Artificial bee colony algorithm
ACO	Ant colony optimization
AGA	Adaptive genetic algorithm
ALO	Ant lion optimizer
ASCSA	Adaptive selective cuckoo search algorithm
BA	Bat algorithm
BB–BCA	Big bang–big crunch algorithm
BBDE	Bare-bones differential evolution
BBPSO	Bare-bones particle swarm optimization
BOFs	Benchmark optimization functions
BRCFA	Binary real-coded firefly algorithm
BTSA	Backtracking search algorithm
CABC-DE	Hybrid chaotic artificial bee colony differential evolution
CKHA	Chaotic krill herd algorithm
CLPSO	Comprehensive learning particle swarm optimization
COA	Coyote optimization algorithm
CSA	Cuckoo search algorithm
CSSA	Charged system search algorithm
DE	Differential evolution
DE–AS	Differential evolution and ant system
DPM	Dynamic programming method
DSA	Differential search algorithm
EMA	Exchange market algorithm
EP	Evolution programming
FA	Firefly algorithm
FPA	Flower pollination algorithm
GBBWCA	Gaussian bare-bones water cycle algorithm
GBTLBO	Gaussian bare-bones teaching learning-based optimization
GSA	Gravitational search algorithm
GSA-CSS	Gravitational search algorithm with original selection
GSA-NHCM	Gravitational search algorithm with new constraint handling method

GWO	Gray wolf optimizer
GWPSO	Particle swarm optimization with inertia weight
HFA-NMS	Hybrid Nelder–Mead simplex-based firefly algorithm
HFVNS	Hybrid stochastic fractal search and variable neighborhood search
HICTS	Hybrid imperialist competitive algorithm and tabu search
HISGA	Hybrid interior search algorithm and genetic algorithm
HKAGA	Hybrid Keshtel algorithm and genetic algorithm
HKASA	Hybrid Keshtel algorithm and simulated annealing
HLGA	Hybrid loop genetic algorithm
HMA	Hybrid metaheuristic algorithm
HMPSO	Hybrid multi-agent particle swarm optimization
HPSO–ICA	Hybrid particle swarm optimization and imperialist competitive technique method
HPSO–TS	Hybrid particle swarm optimization and tabu search
HRDSA	Hybrid red deer algorithm and simulated annealing
HSA	Harmony search algorithm
HSFSA	Hybrid stochastic fractal search and simulated annealing
HSSSA	Hybrid salp swarm algorithm and simulated annealing
HWPSO	Hybrid whale optimization algorithm and particle swarm optimization
HWWGA	Hybrid water wave optimizer and genetic algorithm
ICBO	Improved colliding bodies optimization
IDA	Improved deterministic algorithm
IMA	Improved metaheuristic algorithm
IPG-PSO	Improved pseudo-gradient search-particle swarm optimization
IPM	Interior point method
IQP	Improved quadratic programming
ISA	Interior search algorithm
ISSO	Improved social spider optimization
JA	Jaya algorithm
KA	Keshtel algorithm
LCA	League championship algorithm
LDGWPSO	Particle swarm optimization with linearly decreasing inertia weight
LPM	Linear programming approach
MDE	Modified differential evolution
MFO	Moth flame optimization
MLPM	Mixed-integer linear programming
MNM	Modified Newton method

MORDA	Multi-objective red deer algorithm
MPSO	Modified particle swarm optimization
MSSA	Modified salp swarm algorithm
MSSO	Modified social spider optimization
MTLT–DDE	Modified teaching learning technique and double differential evolution algorithm
NMSFLA	Shuffled frog leaping algorithm and Nelder–Mead
ORCSA	One rank cuckoo search algorithm
PG-PSO	Particle swarm optimization with pseudo-gradient search
PGSWT-PSO	Particle swarm optimization with stochastic weight trade-off and pseudo-gradient search
PSO	Particle swarm optimization
PSO-ALC	Particle swarm optimization with an aging leader and challengers
PSO-CF	Particle swarm optimization with constriction factor
PSO-GT	Particle swarm optimization with graph theory
PSO-TVAC	Particle swarm optimization with time-varying acceleration coefficients
PSO-TVIW	Particle swarm optimization with time-varying inertia weight
QODE	Quasi-oppositional differential evolution
QOTLBO	Quasi-oppositional teaching learning-based optimization
RCGA	Real-coded genetic algorithm
RDA	Red deer algorithm
RSGA	Genetic algorithm with rank selection technique
SARCGA	Self-adaptive real-coded genetic algorithm
SEO	Social engineering optimizer
SFOA	Sunflower optimization algorithm
SFS	Stochastic fractal search
SGA	Specialized genetic algorithm
SPSO-TVAC	Particle swarm optimization with time-varying acceleration coefficients
SPSO-TVAC	Particle swarm optimization with self-organization and time-varying acceleration coefficients
SSA	Salp swarm algorithm
SSO	Social spider optimization
SWT-PSO	Particle swarm optimization with stochastic weight trade-off
TVAC	Time-varying acceleration coefficients
WOA	Whale optimization algorithm
WWO	Water wave optimizer

1 Introduction

Optimal reactive power dispatch (ORPD) is one of the most popular optimization problems in engineering field in aim to operate power systems stably and effectively. ORPD is mathematically formulated as a nonlinear problem where objective function and constraints are shown clearly. In fact, the task of such ORPD problem is to determine control parameters in electricity power systems such as voltage of generation buses, tap setting of transformers and generated reactive power of capacitor banks so that other obtained working parameters such as voltage of load buses, apparent power flow of transmission lines and reactive power of generators are always within an predetermined allowed working range. ORPD problem focuses on optimizing different independent objectives consisting of total active power losses in all transmission lines, voltage deviation and voltage stability index. As the three objectives are obtained, the considered power systems are working economically and stably. Similar to other optimization problems related to power systems such as economic load dispatch [1, 2] and optimal power flow [3, 4], ORPD has also attracted the use of conventional deterministic methods and modern metaheuristic methods. The applications of classical deterministic methods have been carried out in refs. [5–11] while a huge number of applications of standard metaheuristic (SMH), improved versions of SMH (ISMH) and hybrid methods have been presented in Ref. [12]–Ref. [54]. Among these metaheuristic, there some large algorithm groups such as particle swarm optimization (PSO) variants [12–21], differential evolution (DE) variants [22–26], genetic algorithm (GA) variants [27–31] and gravitational search algorithm (GSA) variants [32–35]. In addition, many other standard methods as well as improved methods have been employed for dealing with ORPD problem and presented in [36–54].

It is clear that there are a huge number of studies regarding ORPD problem; however, the obtained results have not been good enough and many researchers have constantly developed optimization tools for tackling main drawbacks such as low optimal solution quality, long computation time and difficult task of tuning the most appropriate control parameters. For suggesting one of the most appropriate optimization methods to find the effective solution for an ORPD problem, we have collected and summarized several popular and powerful methods applied to various optimization problems in recent years as in Table 1. In the table, we emphasize the type of methods and the applied optimization problems for discussion of the application and potential search ability of methods. Most the solution methods can be classified into three types

Table 1 Popular and state-of-the-art metaheuristic algorithms

No.	Heuristic algorithm	Type	References	Published year	Studied problem
1	PSO	Origin	[55]	1995	BOFs
2	BA	Origin	[56]	2010	BOFs
3	FA	Origin	[57]	2008	BOFs
4	CSA	Origin	[58]	2009	BOFs
5	FPA	Origin	[59]	2012	BOFs
6	SSO	Origin	[60]	2013	BOFs
7	KA	Origin	[61]	2013	–
8	ISA	Origin	[62]	2014	BOFs
9	WWO	Origin	[63]	2015	BOFs
10	SFSA	Origin	[64]	2015	BOFs
11	WOA	Origin	[65]	2016	BOFs
12	RDA	Origin	[66]	2016	BOFs
13	MSSO	Improved	[67]	2016	Economic dispatch problem
14	MSSO	Improved	[68]	2017	Inverse radiation and coupled radiation–conduction heat transfer problems
15	MSSO	Improved	[69]	2017	Number attribute reduction problem
16	COA	Origin	[70]	2018	BOFs
17	SFOA	Origin	[71]	2018	BOFs
18	SEO	Origin	[72]	2018	BOFs
19	HWWGA	Hybrid	[73]	2018	A bi-objective partial interdiction problem
20	HWPSO	Hybrid			
21	HISGA	Hybrid	[74]	2018	Distribution network problem
22	HKSA	Hybrid			
23	MORDA	Improved	[75]	2018	Three-objective function problem
24	HRDSA	Hybrid	[76]	2018	Sustainable closed-loop supply chain network design problem
25	HKAGA	Hybrid			
26	HICTS	Hybrid			
27	HKASA	Hybrid	[77]	2018	Tire closed-loop supply chain network design problem.
28	HFVNS	Hybrid			
29	HSFSA	Hybrid			
30	SSA	Origin	[78]	2018	Engineering design problems
31	MSSA	Improved	[79]	2018	Bi-objective green home healthcare routing problem
32	HSSSA	Hybrid			
33	ASCSA	Improved	[80]	2018	Optimal operation of hydrothermal power systems

including original versions, improved versions and hybrid versions, in which the original versions and improved versions only aim to single methods with their drawbacks and the improvements have been proposed while the hybrid methods are based on the coordination of two different methods or more. A view from the applied problems can reveal that the potential search ability of these methods could not be demonstrated persuasively due to the lack of challenges from complicated constraints and large-scale problems. The simplest problem in the table is the benchmark optimization functions (BOFs), which have been solved by many original, improved methods and hybrid

methods. Hybrid methods have been employed for more complicated problems such as sustainable closed-loop supply chain network design, tire closed-loop supply chain network design, bi-objective green home healthcare routing problem and economic load dispatch. These hybrid methods have shown more promising than the original ones for such problems, but the application of these methods has become more difficult due to the coordination of different individual methods. More control parameters and more computation steps are the common characteristics of hybrid ones. On the other hand, these methods can be divided into three groups with one, two and three new solution

generations per iteration. Normally, one new solution generation-based methods tend to produce new solutions at the same time with the same manner while two and three new solution generations-based methods produce more new solutions by using two or three different operations and take more time for their search process. In the table, PSO, FA, FPA, ISA, WOA, SFOA, SSA, HWPSO and HISGA methods are the family of the first group while the third group consists of the improved and hybrid versions regarding SFS methods and SSO methods. The rest is belonging to the second group with two new solutions generations. For the first method group, the search strategy is not diversified since the whole population is newly updated by using the same way or the same formula. PSO method is an example of the main drawback falling into local optimum zones with low quality. FPA method seems to be more effective than PSO since one of two different ways can be employed for each newly updated solution. The main task of the FPA method is to select the most appropriate formula, which is dependent on the used probability. The standard algorithms such as SFOA and SSA and other hybrid methods including HWPSO and HISGA were developed in the early this year. These hybrid methods have been developed with the intent to take advantages of element methods and avoid overlapping shortcomings of each one. Among these methods with two new solution generations per iteration, cuckoo search algorithm (CSA) is one of the most effective optimization ones. This method has been judged by solving a set of benchmark functions and compared to PSO and GA. In the early this year, its new improved version [80] was introduced for finding the optimal operation of power systems with hydropower and thermal power plants. The improved method has demonstrated its outstanding performance since its found better objective than most popular methods such as evolutionary family (DE variants, EP, GA variants) and swarm family (CSA variants and PSO variants). The outcomes with respect to the most effective solution and stabilization search ability have resulted in a confirmation that these methods could be better than other compared methods. Among the methods with three new solutions generations introduced in the table, SSO was first introduced in 2013 by Cuevas et al. [60]. The SSO has a special characteristic which is totally different from other methods. It consists of three new solution generations per iteration but the number of newly updated solutions per iteration is not high, about approximately the population size. The search strategy of this method effectively exploits the solution space by dividing the population size into two different groups, female and male groups. In addition, the offspring in this method is also produced in the case of occurred mating operation. Females perform the movement action first in the first generation and then males continue

to move to new positions in the second generation. The new positions of females are dependent on the closet spider to them and the best spider in the population in addition to the weight of these related spiders and the distance between them and the considered females. Similarly, the new positions of male spiders are determined based on the closest female to him or all other males. The specialization of the SSO is the third new generation, which can use both good males and females to produce offspring (new solutions). Unlike other methods in Table 1, the search strategy of SSO can focus on the global search by the first and the second new solutions while the local search is strongly exploited by the third new solution. Compared to other methods such as PSO, BA, CSA, SSA, MSSA and FPA, SSO has more control parameters and more complicated implementation but these issues become simpler compared to hybrid methods. In fact, hybrid methods are developed by integrating two or more individual methods. Thus, these methods have basically more control parameters and operations for applications. It is obvious that the SSO can be a very optimization algorithm for searching for optimal solutions if these drawbacks can be successfully handled. In [60], the SSO has shown its potential search since several advantages over ABC and PSO have been indicated clearly and persuasively such as better optimal solutions and smaller standard deviation. Nevertheless, such achievements have not met the requirements of complicated optimization problems in different engineering fields. Other authors in [66–69] have pointed out drawbacks that such method has been put up with such as low convergence speed to global optimum and long computation process. Thus, they have proposed different changes for overcoming such limitations and lead to better results. For instance, authors in [67] have applied mutation procedure of standard DE for searching new solutions. These authors have canceled the gender of spiders, and there were no longer movements of females and males as well as mating procedure of producing baby spiders. Four improved SSO methods have been proposed in [68] by using constriction factor, inertia weight factor of PSO variants in [17], and other modifications such as adding one more updated step size and using mutation operation of DE for carrying out mating operation. Clearly, such proposed methods in [68] were the integration of PSO variants and SSO, and DE variants and SSO. In [69], authors have suggested two changes in which the first change was to update the best solution continuously after each new solution was produced and the second change was to construct a new fitness function for more accurate evaluation. The impact of the two changes could see clearly and effectively since results obtained were much better than those from SSO. However, the method has consumed more time for performing all computation stages of SSO in addition to taking time for

continuously updating the best solution. Such methods have been proved better than SSO and other existing methods through heat transfer problems with respect to better accuracy and better stabilization. In spite of good results, the methods have also coped with the following limitations: (1) high number of control parameters; (2) spending more time tuning the best values of the control parameters; (3) long computation time due to many computation steps. It is clearly acknowledged that the methods in [67–69] have different difficulties to be considered as a potential optimization tool. Consequently, in the paper, we propose a novel improved SSO method by performing:

1. Modification on the first new solution generation: In SSO, two equations are proposed for updating new solutions but in the proposed method only one equation is used and modified before application.
2. Modification on the second new solution generation: Similar to the first new solution generation, SSO also uses two equations for the second generation; however, only one equation should be used and modified before application in the proposed method.

With respect to the proposed method, our main contributions in the article are as follows:

1. Reducing one control parameter, so time of tuning the parameter is zero and simulation time is shortened.
2. Reducing both computation processes and comparison condition, so simulation time can be shortened.
3. Enabling the proposed method to find better optimal solutions with faster convergence speed.
4. Implementing other methods such as FA, PSO, CSA, FPA, SSO, SSA, MSSA and HSSSA for demonstrating the potential search of the proposed method.

The performance of the proposed ISSO method is investigated in the paper by solving benchmark functions, IEEE 30-bus system and IEEE 118-bus system with three single objectives consisting of power loss minimization, voltage deviation minimization and voltage stability maximization. Obtained results by the proposed method and other ones are compared to evaluate capability of searching optimal solutions, stabilization of search ability and search speed of the proposed method. The structure of the paper is as follows: Literature review is presented in Sect. 2. The optimization problem with objective functions and constraints is described in Sect. 3. The standard SSO and proposed method are explained in Sect. 4. The implementation of the proposed method for the solved problem is given in Sect. 5. Simulation results from benchmark functions and two IEEE power systems are given in Sect. 6. Finally, conclusions are summarized in Sect. 7.

2 Literature review

ORPD problem has a very important role in operation field of power systems and attracted the concern of a huge number of researchers. For dealing with complicated constraints and finding optimal solutions of different single objectives of ORPD problem, the researchers have used different optimization tools such as origin deterministic algorithms, origin metaheuristic algorithms, improved metaheuristic algorithms and hybrid metaheuristic algorithms. Better literature review of applied methods, studied power systems, considered objective function and other implemented methods for comparison are given in Table 2. In the table, we can see five types of methods including original deterministic algorithm (ODA), improved deterministic algorithm (IDA), original metaheuristic algorithm (OMA), improved metaheuristic algorithm (IMA) and hybrid heuristic algorithm (HMA) that have been successfully applied for ORPD problem. Among these methods, ODA and IDA [5–11] are the oldest methods with a small number of applications and their applications have ended recent years. On the contrary, metaheuristic algorithms such as particle swarm optimization (PSO) variants [12–21], differential evolution (DE) variants [22–26], genetic algorithm (GA) variants [27–31], gravitational search algorithm (GSA) variants [32–35] and other methods [36–54] have shown their leading ability with a high number of applications, especially improved and hybrid metaheuristic algorithms have been constantly developed recent years. Almost studies have considered power loss (PL) as a main objective and optimization methods have been evaluated by comparing the value. A few studies have focused on the installation of shunt capacitors and their initial capital has been considered to be a main objective function. For better evaluations, other studies have taken power quality factors including voltage deviation (VD) and voltage enhancement index (L index). The review on test cases can indicate that real power systems such as Indian 24-bus system, Brazil system, North America system, Taiwan system, 810-bus system and 135-bus system have not been studied widely and only considered in the first studies by using the oldest methods. Most data of the systems have not been shown in the published work. Only IEEE 30-bus and 118-bus have been taken into account in approximately all the studies because all the data of the systems have been reported sufficiently. IEEE 6-bus, 14-bus and 57-bus systems have been employed in few studies because of different reasons. IEEE 6-bus and 14-bus systems are small-scale tests for demonstrating the strong search ability of methods while IEEE 57-bus system has ignored the limitations of all branches. Consequently, we have used the two most popular systems, IEEE 30-bus

Table 2 Review on previous studies about ORPD problem

Method	Type of method	Other implemented methods for comparisons	Objective function	Test cases
MNM [5]	IDA	DPM	PL	IEEE 30-bus system, 810-bus system
LPM [6]	ODA	–	PL	IEEE 30-bus system
MLPM [7]	IDA	–	Capacitor installation cost	135-bus system
IPM [8]	ODA	–	PL	Brazil system, North America system
IPM [9]	ODA	–	PL	IEEE 6-bus and 118-bus system
DPM [10]	ODA	Software	VD	Taiwan system
IQP [11]	IDA	QPM, LPM	PL	IEEE 30-bus and 118-bus system
HMPSO [12]	HMA	GA, PSO HPSO, MPSO	PL	IEEE 30-bus and 118-bus system
CLPSO [13]	IMA	PSO	PL, L index	IEEE 30-bus and 118-bus system
HPSO–TS [14]	HMA	TSA, PSO	PL, VD	IEEE 30-bus system
PSO-ALC [15]	IMA	PSO	PL, VD	IEEE 30-bus, 57-bus and 118-bus system
PSO [16]	OMA	–	VD	Southern India 24-bus system
IPG-PSO [17]	IMA	PSO-TVIW, PSO-TVAC, SPSO-TVAC, PSO-CF, PG-PSO, SWT-PSO, PGSWT-PSO	PL, VD, L index	IEEE 30-bus and 118-bus systems
SPSO-TVAC [18]	IMA	–	PL	IEEE 14-bus and 118-bus system
HPSO–ICA [19]	HMA	PSO, ICA	PL, VD	IEEE 57-bus and 118-bus system
PSO [20]	OMA	LPM	VD	New England 39-bus system
PSO-GT [21]	IMA	PSO, GA	PL	IEEE 14-bus system
DE [22]	OMA	–	PL, VD, L index	IEEE 30-bus system
DE–AS [23]	HMA	EP, PSO, DE	PL	IEEE 30-bus system
MTLT–DDE [24]	HMA	ACO, DE, ABC, LCA, CSSA, BRCFA, BB–BCA, PBILA	PL	IEEE 14-bus, 30-bus and 118-bus systems
QODE [25]	IMA	DE	PL, VD, L index	IEEE 30-bus, 57-bus and 118-bus test systems
CABC-DE [26]	HMA	DE	PL	IEEE 14-bus and 30-bus systems
AGA [27]	IMA	GA	PL	IEEE30-bus system
SARCGA [28]	IMA	EP	PL	IEEE 14-bus and 30-bus systems
HLGA [29]	IMA	GA	PL	IEEE 14-bus system
SGA [30]	IMA	–	PL, VD	IEEE 30-bus and 57-bus systems
RSGA [31]	IMA	NRM	PL	IEEE 30-bus system
GSA [32]	OMA	–	PL, VD, L index	IEEE 30-bus, 57-bus and 118-bus systems
GSA [33]	OMA	–	Multi-objective (PL and VD)	IEEE 57-bus and 118-bus systems
GSA [34]	OMA	–	PL, VD, L index	IEEE 14-bus and 30-bus systems
GSA-NHCM [35]	IMA	GSA, PSO, GSA-CSS	PL, VD	IEEE 14-bus, 30-bus and 57-bus systems
ACO [36]	OMA	GA, PSO	PL	IEEE 14-bus and 30-bus systems

Table 2 (continued)

Method	Type of method	Other implemented methods for comparisons	Objective function	Test cases
ACO [37]	OMA	LPM	PL	Indian 24-bus system
QOTLBO [38]	IMA	TLBO	PL, VD, L index	IEEE 30-bus and 118-bus systems
GBTLBO [39]	IMA	BBDE, BBPSO	PL	IEEE 14-bus and 30-bus systems
CSA [40]	OMA	MFO, GWO, FA, FPA, GSA	PL	IEEE 30-bus system
ORCSA [41]	IMA	–	PL, VD, L index	IEEE 30-bus and 118-bus systems
HSA [42]	OMA	–	PL, VD, L index	IEEE 30-bus and 57-bus systems
NMSFLA [43]	IMA	PSO, GWPSO, LDGWPSO, MDE	PL	IEEE 30-bus and 57-bus systems
CKHA [44]	IMA	KHA	PL, VD, L index	IEEE 30-bus and 57-bus systems
HFA-NMS [45]	HMA	PSO, ABC, FA	PL, VD	IEEE 30-bus and 118-bus systems
GWO [46]	OMA	SGA, PSO, HSA	PL, VD	IEEE 30-bus and 118-bus systems
ABCA [47]	OMA	LPM	PL	Indian 24-bus system
EMA [48]	OMA	–	PL, VD, L index	IEEE 30-bus and 118-bus systems
DSA [49]	OMA	–	PL, VD, L index	IEEE 30-bus and 57-bus systems
ALO [50]	OMA	BA, GWO, ABC	PL, L index	IEEE 30-bus and 118-bus systems
BTSA [51]	OMA	–	Multi-objective (PL and VD)	IEEE 30-bus system
ICBO [52]	IMA	CSA, PSO, GSA	PL	IEEE 57-bus system
GBBWCA [53]	IMA	WCA	PL, VD	IEEE 30-bus, 57-bus and 118-bus systems
JA [54]	OMA	–	PL, capacitor installation cost	IEEE 30-bus system
Proposed method	IMH	FA, CSA, PSO, FPA, SSO, SSA, MSSA, HSSSA, KA	PL, VD, L index	Benchmark functions, IEEE 30-bus and 118-bus systems

and 118-bus systems and three single objective functions including PL, VD and L index have been considered to be main targets for comparisons. In addition, we have also used benchmark optimization functions for general comments on the performance of proposed method. Many studies have implemented only one proposed method for solving ORPD problem and compared results with previous methods rather than implement more methods. As observed from information of other implemented methods for comparisons, deterministic methods in [5–11] have not focused on comparison of performance but the demonstration of solving ORPD problem exactly. Studies in [5] and [11] have implemented other methods for comparisons of performance, and study in [10] has shown DPM could deal with the same system as well as software could accomplish.

HMPSO [12] is the integration of GA, multi-agent system and conventional PSO. Thus, HMPSO has the characteristic of hybrid PSO-GA and of multi-agent PSO. The method is superior to other methods implemented methods including GA, PSO, HPSO and MPSO. CLPSO

[13] has applied a learning strategy in aim to tackle the premature convergence that has been existed in the feature of PSO. The method has proposed a new formula for determining the values of inertia weight and has suggested a new range for velocity, which was totally different from other PSO methods. Compared to GA and PSO, both HMPSO and CLPSO were capable of avoiding premature convergence to local optimum with low quality and had other advantages such as high success rate, stable convergence feature and accurate solutions. However, the further performance of the two methods was not clear and persuasive because all comparisons were simply made with GA, PSO and a small number of other methods such as linear programming and evolutionary programming. Furthermore, only objective of minimizing power loss was considered for comparison. HPSO–TS was developed in [14] by the use integration of search function of PSO and TS. PSO has acted as global search while TS has been in charge of local search and stopping PSO from falling into local optimum fast. So, the search process of HPSO–TS

was much more complicated than PSO and TS, and there were two new solution generations for each iteration in HPSO–TS. This was totally different from the feature of PSO and TS. Via the comparison of results obtained from IEEE30-bus system with the objective of power loss minimization, HPSO–TS has shown better search ability than other methods such as standard DE, PSO and TS. Clearly, the investigation of the method's performance has been restricted. The conventional PSO has been applied in [16] and [20] for the voltage profile improvement. The work here only demonstrated the ability of PSO for dealing all constraints and the ability of finding better optimal solution than linear programming method. Another improved version of PSO, PSO-ALC has been applied to ORPD problem in [15] for independently minimizing power loss and voltage deviation. PSO-ALC has used a leader particle to attract other particles for moving new positions. If new positions have been improved in terms of fitness function, the leader has been employed for the next step. Otherwise, new solutions would be merged into the whole population for determining another leader particle. The method has been tested on different cases and has been considered as the best method among all compared methods.

Many existing improved versions of PSO in addition to IPG-PSO have been applied in [17] for ORPD problem with three independent objectives consisting of power loss, voltage deviation and voltage stabilization index. IPG-PSO has been constructed by applying pseudo-gradient theory for determining the best velocity direction, which is totally different from all previous versions of PSO. The pseudo-gradient could support to find better updated velocity, leading to better optimal solution. As a result, the method has outperformed other PSO methods consisting of PSO-TVIW, PSO-TVAC, SPSO-TVAC, PSO-CF, PG-PSO, SWT-PSO and PGSWT-PSO. SPSO-TVAC has also been applied in [18] for ORPD problem with different data from [17]. HPSO–ICA has been proposed in [19] by the integration of imperialist competitive algorithm and improved PSO. The imperialist competitive algorithm can enable to select promising solutions for producing new solutions. The method has produced new positions and evaluated fitness functions three times; thus, it has taken much more time than PSO for the whole search process. In fact, the simulation time reported in [19] has given the evidence for the comment since the simulation time of HPSO–ICA was much longer than that of PSO and ICA for all test cases. Although better results were obtained, the advantages of HPSO–ICA over PSO and ICA were not able to be accepted. In [21], graph theory has been applied in the improved PSO called PSO with graph theory (PSO-GT) for the duty of fault detection and isolation in an integrated system of thermal units and wind turbines. The proposed method has succeeded to deal with all the constraints.

Different versions of DE have been reemployed or proposed for ORPD such as standard DE [22], DE–AS [23], MTLT–DDE [24], QODE [25] and CABC-DE [26]. Such methods have been improved mainly based on modifications on mutation operation and combination of other methods and DE for overcoming several limitations of DE such as easily fallen into local optimal solutions, premature convergence and weakly jumping out local traps. DE–AS has applied ant system to replace existing selection operation of DE. Besides, mutation factor has been also considered as a variable and determined by using three different conditions. The proposed method has also seen its advantages over PSO and DE via IEEE 30-bus system with the target of minimizing power loss. MTLT–DDE was an integration of modified teaching learning technique (MTLT) and double differential evolution (DDE). MTLT has changed the search strategy into a number of points instead of only one point like the standard teaching learning technique while DDE has used new mutation, new crossover and new selection operations. MTLT–DDE has been compared to almost recent methods via the results obtained from IEEE 30-bus and IEEE 118-bus systems. Simple comparison via power loss could see that method was better than all other methods; however; convergence speed has not been demonstrated for further investigation.

GA and its improved versions have been applied for ORPD such as AGA [27], SARCGA [28], HLGA [29], SGA [30] and RSGA [31]. In AGA, mutation probability and crossover probability have been adaptively tuned dependent on fitness value of population in aim to enable AGA jump out local search with premature convergence and low-quality solutions. In SARCGA, simulated binary crossover has been used as self-adaption and RCGA with probability distribution (namely polynomial function) has been used to replace uniform distribution. The demonstration of SARCGA's performance has not satisfied readers since comparisons have been made with EP and DE. HLGA has determined good search zone and started search process within the identified zones. Then, HLGA has focused on global search within the identified zones. Thus, compared to GA, the method has found better optimal solution with faster speed. Nevertheless, the method has coped with a limitation that the capability of jumping out local zone was weak and it has been fallen into local optimum easily. The performance of standard GA with Roulette wheel selection and the performance of improved GA with rank selection technique have been analyzed by running on IEEE 30-bus system. The rand selection technique that has retained the top solutions among all old and all new solutions was superior to GA with roulette wheel selection. The method has been only compared to GA, and its performance is still a question for readers.

In addition to the three largest method groups, other small groups have been applied for ORPD problem such as GSA [32–34], GSA-NHCM [35], ACO [36, 37], QOTLBO [38], GBTLBO [39], CSA [40], ORCSA [41], HSA [42], NMSFLA [43], CKHA [44], HFA-NMS [45], GWO [46], ABCA [47], EMA [48], DSA [49], ALO [50], BTSA [51], ICBO [52], GBBWCA [53] and JA [54]. Among these methods, CSA, GBBWCA and JA are the latest methods which have been applied for dealing different systems of ORPD problem. In general, all studies have made a big effort for demonstrating their applied or proposed methods; however, most methods have been only compared to a few methods consisting of GA, PSO and standard methods. Furthermore, the probability has been only carried out by comparing one objective only while comparison of convergence speed has been almost ignored. In the paper, we investigate the performance of compared methods by using reliable comparison criteria and result in the conclusion which can advise readers which good methods for application. In addition to implementation of the proposed method, we also run other methods for better performance evaluation consisting of PSO [55], FA [57], CSA [58], FPA [59], SSA [78], MSSA [79] and HSSSA [79].

3 Optimal reactive power dispatch problem

3.1 Description

A transmission power network is the connection of electric components such as power plants, transformers, transmission lines, capacitors and loads. Among the objects, power plants are in charge of produce electricity and transmit the electricity to transformers. There are two types of transformer, step-up transformer and step-down transformer. Step-up transformers receive medium voltage from generators in power plants and increase the voltage to higher level and transfer electricity to transmission lines but step-down transformers receive electricity with very high voltage from transmission lines and decrease the voltage to lower level compatible with the requirement from loads. Transmission lines can be hundreds of kilometers long with the main duty of providing electricity to loads or transformers. The transmission power network can work stably and effectively if all the components are controlled appropriately. Basically, power plants are represented by generators with three main parameters consisting of active power output, reactive power output and voltage. Transformers have two main roles in the contribution to the stable operation of the transmission power network such as increasing or decreasing voltage and regulating voltage by setting tap changer. Transmission lines are represented by impedance and admittance but its important factor

influencing the stable operation of the transmission power network is maximum apparent power flow limit. If apparent power flow through transmission lines is not higher than their capacity, they are working stably; however, it cannot conclude the status of the transmission power network. Capacitors are used to provide active power to loads with intent to reduce power loss and regulate voltage of buses. The transmission power network is working stably if all electric components as well as their operating parameters are in allowed operating range. Thus, the major role of solving ORPD problem is to determine these main parameters of electric component so that the transmission power network can work stably and effectively. ORPD problem is solved by using mathpower program and the support of optimization tools. The optimization tools provide the program with control variables with standard values (i.e., main parameters in allowed range). Then, the program is run and all remaining variables (i.e., other parameters) are obtained as a result. The optimization tool will calculate the effectiveness of given objectives as well as judge operating status of electric components. Finally, these control variables will be changed close to the most appropriate values.

3.2 Assumption

ORPD problem considers six electric components such as (1) generators of power plant; (2) transformers; (3) transmission lines; (4) capacitors; (5) loads; and (6) buses. Each component has main parameters regarding to stably operating status of transmission power network. These parameters are explained and supposed as follows:

1. Generators: active power output, reactive power output and voltage can be regulated smoothly. It means that generators can work as parameters obtained from optimization tools and Mathpower program.
2. Transformers: tap changer is controlled exactly and expected voltage can be responded.
3. Transmission lines: maximum apparent power flow limit is predetermined and during working time, other parameters of the line such as impedance and admittance do not suffer from the impact of environment temperature.
4. Capacitors: reactive power can be exactly generated as requirement.
5. Loads: active power and reactive power are exactly known and they remain unchanged during considered time.
6. Buses: voltage magnitude and voltage phase angle can be measured exactly.

On the other hand, ORPD problem supposes that all generators are working by given values of active power

output. During the operation process, only voltage and reactive power output can be tuned by operators.

3.3 Problem formulation

ORPD problem is mathematically formulated by the present of objectives and constraints. Objectives can be minimization of power loss, minimization of voltage deviation and minimization of voltage stability L index while constraints are voltage limitations of load buses, apparent power flow of transmission lines, reactive power of generators and the balance between demand and supply in terms of active power and reactive power. The objectives and constraints are described as follows:

3.3.1 Objective functions

Active power loss minimization Active power loss is also the electricity energy loss leading to less effective economy of power systems and high price of energy for customers. As a result, the total active power loss is considered as a main objective when operating power systems. The objective is formulated as follows:

$$\text{Minimize } F_1 = \sum P_{\text{loss}} \tag{1}$$

where $\sum P_{\text{loss}}$ is the real power loss obtained by the following equation:

$$\sum P_{\text{loss}} = \sum_{i=1}^{N_{\text{bus}}} \sum_{\substack{j=1 \\ j \neq i}}^{N_{\text{bus}}} g_{\text{line}l} \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\varphi_i - \varphi_j) \right] \tag{2}$$

where $g_{\text{line}l}$ is the conductance value of line l connecting two buses i and j; φ_i and φ_j represent the voltage phase angles of buses i and j, respectively.

Load bus voltage deviation minimization The load bus voltage can show the voltage profile of power systems. In case that the load voltage changes continuously and its value is much lower or higher than expected value 1.0 pu, the power system is working unstably and ineffectively. Thus, the second objective is to minimize the deviation of load voltage magnitude. Namely, the objective is expressed by the following model:

$$\text{Minimize } F_2 = \sum_{i=1}^{N_{\text{load}}} |V_{\text{load}i} - V_{\text{ref}}| \tag{3}$$

where $V_{\text{load}i}$ is the ith load's voltage magnitude; V_{ref} is the hopeful value of load voltage, which is normally set to 1.0 pu.

Voltage stability L index minimization In power system, loads tend to change their consumed active power almost

continuously. This phenomenon can result in uncontrolled condition of power systems, and even it can result in voltage collapse. Normally, L index is within the range [0; 1]. "0" value indicates that all loads and such power network are working stably but "1" value indicates that such power network is being subjected to disturbance condition and voltage collapse can take place soon. Thus, the improvement in voltage stability can be yielded in case minimization of L index is obtained [11]. The third objective concerned in the paper is to minimize voltage stability index (L index) of all buses similar to the maximization of voltage stability. The objective and L index can be seen by the following formulas:

$$\text{Minimize } F_3 = \max(L_i); i = 1, \ldots, N_{\text{bus}} \tag{4}$$

where L_i is the L index value of bus i determined by [11]:

$$L_i = \left| 1 - \frac{\sum_{j=1}^{N_G} Y_{ij}V_j}{V_i} \right|; \ i = 1, 2, \ldots, N_{\text{bus}} \tag{5}$$

where Y_{ij} is the mutual admittance between bus i and bus j.

3.3.2 Constraints

Real and unreal power balance constraints In order to ensure voltage and frequency are within working range values, real power and reactive power must be balanced between generating and consuming. The constraints are seen in the following equations:

$$P_{Gi} - P_{di} = V_i \sum_{j=1}^{N_{\text{bus}}} V_j \left[G_{\text{line}l} \cos(\varphi_i - \varphi_j) \right. \\ \left. + B_{\text{line}l} \sin(\varphi_i - \varphi_j) \right]; \ i = 1, \ldots, N_{\text{bus}} \tag{6}$$

$$Q_{Gi} + Q_{ci} - Q_{di} = V_i \sum_{j=1}^{N_{\text{bus}}} V_j \left[G_{\text{line}l} \sin(\varphi_i - \varphi_j) \right. \\ \left. - B_{\text{line}l} \cos(\varphi_i - \varphi_j) \right]; \ i = 1, \ldots, N_{\text{bus}} \tag{7}$$

where $G_{\text{line}l}$ and $B_{\text{line}l}$ are real and imaginary parts of admittance of line l connecting buses i and j, respectively.

In addition to the equality constraints above, other inequality constraints related to working limitations of other electric components are also taken into account in ORPD problem. Namely, such inequality constraints are considering the upper and lower limitations of: (1) reactive power generation and voltage magnitude of generator; (2) the reactive power generation of VAR compensator; tap changer of transformer; voltage magnitude of load; and the maximum apparent power flow of branch l. Such constraints are given in the following formulas:

$$Q_{Gi,\min} \leq Q_{Gi} \leq Q_{Gi,\max}; \ i = 1,\ldots,N_G \tag{8}$$

$$V_{Gi,\min} \leq V_{Gi} \leq V_{Gi,\max}; \ i = 1,\ldots,N_G \tag{9}$$

$$Q_{ci,\min} \leq Q_{ci} \leq Q_{ci,\max}; \ i = 1,\ldots,N_c \tag{10}$$

$$T_{i,\min} \leq T_i \leq T_{i,\max}; \ i = 1,\ldots,N_t \tag{11}$$

$$V_{\text{load}i,\min} \leq V_{\text{load}i} \leq V_{\text{load}i,\max}; \ i = 1,\ldots,N_{\text{load}} \tag{12}$$

$$S_l \leq S_{l,\max}; \ l = 1,\ldots,N_{\text{line}} \tag{13}$$

4 The proposed ISSO method

4.1 Original social spider optimization algorithm

The social spider optimization (SSO) is also a metaheuristic algorithm such as PSO, GA and DE; however, the configuration of SSO is different from these methods. In fact, these methods have only one time producing new solutions but SSO possesses three new solution generations. The first generation and the second generation, respectively, produce N_{fs} and N_{ms} new solutions. The third generation produces N_{bs} new solutions in which N_{bs} is the number of baby spiders. Normally, the number of females accounts for from 60 to 90% of the whole spider community (N_{pop}). The three generations of SSO are described in detail as follows.

The first generation (the movement of female spiders) The first generation produces N_{fs} new solutions via the phenomenon of position movement of all female spiders. In the spider community, all female spiders will move first when there is a vibration on the web. New position of female spider f called $X_{\text{fs},f}$ is dependent on both the vibration intensity and the position of (1) one spider who is closest to her and (2) the best spider who has the best weight. Thus, the new position of female spider f is obtained by using either Eqs. (14) or (15) depending on the movement probability P_m. If a random number RN_f within 0 and 1 arbitrarily produced is higher than P_m, Eq. (14) is applied for moving spider f. Otherwise, Eq. (15) is employed for determination of the new position of spider f.

$$\begin{aligned} X_{\text{fs},f} = X_{\text{fs},f} + \text{rand} \cdot \text{Vib}_{\text{nearest}} \cdot (X_{\text{nearest}} - X_{\text{fs},f}) + \text{rand} \\ \cdot \text{Vib}_{\text{Gbest}} \cdot (X_{\text{Gbest}} - X_{\text{fs},f}) + \text{rand} \cdot (\text{rand} - 0.5) \end{aligned} \tag{14}$$

$$\begin{aligned} X_{\text{fs},f} = X_{\text{fs},f} - \text{rand} \cdot \text{Vib}_{\text{nearest}} \cdot (X_{\text{nearest}} - X_{\text{fs},f}) - \text{rand} \\ \cdot \text{Vib}_{\text{Gbest}} \cdot (X_{\text{Gbest}} - X_{\text{fs},f}) + \text{rand} \cdot (\text{rand} - 0.5) \end{aligned} \tag{15}$$

In Eqs. (14) and (15), some symbols need to be defined as follows: $\text{Vib}_{\text{nearest}}$ and X_{nearest} are the vibration intensity and position of the spider closest to female spider f; $\text{Vib}_{\text{Gbest}}$ and X_{Gbest} are the vibration intensity and position of the global best spider in the whole population.

The vibrations of the two spiders are calculated by the following expressions:

$$\text{Vib}_{\text{nearest}} = w_{\text{nearest}} \cdot e^{-d^2_{f,\text{nearest}}} \tag{16}$$

$$\text{Vib}_{\text{Gbest}} = w_{\text{Gbest}} \cdot e^{-d^2_{f,\text{Gbest}}} \tag{17}$$

where $d_{f,\text{nearest}}$ and $d_{f,\text{Gbest}}$ are, respectively, the distance between considered female spider f and another one closest to her and the distance between considered female spider f and the best spider; w_{nearest} and w_{Gbest} are, respectively, the weight of the nearest spider to spider f and the weight of the global best spider in which the weight of a typical spider s can be calculated by

$$w_s = \frac{\text{FV}_{\text{Gworst}} - \text{FV}_s}{\text{FV}_{\text{Gworst}} - \text{FV}_{\text{Gbest}}} \tag{18}$$

where $\text{FV}_{\text{Gworst}}$ and FV_{Gbest} are the highest fitness value of the global worst spider and the lowest fitness value of the global best spider, and FV_s is the fitness value of spider s, which is being considered;

The second generation (the movement of male spiders) After all the female spiders change their position (corresponding to N_{fs} new produced solutions), all male spiders also move to new positions corresponding to producing N_{ms} new solutions. However, the movement strategy of male spiders is not the same as that of female spiders. New position of being considered male spider m is dependent on either the female closest to him or all other males as shown in Eqs. (19) and (20). Obviously, it needs condition for using either (19) or (20) similar to the use condition of Eqs. (14) and (15). Namely, the weight of being considered male spider m $w_{\text{ms},m}$ is compared to the medium weight of all males $w_{\text{ms,mean}}$. If $w_{\text{ms},m}$ is higher than $w_{\text{ms,mean}}$, male spider m will employ Eq. (19) for changing its position. On the contrary, Eq. (20) is selected for the movement.

$$\begin{aligned} X_{\text{ms},m} = X_{\text{ms},m} + \text{rand} \cdot \text{Vib}_{\text{fs,nearest}} \cdot (X_{\text{fs,nearest}} - X_{\text{ms},m}) \\ + \text{rand} \cdot (\text{rand} - 0.5) \end{aligned} \tag{19}$$

$$X_{\text{ms},m} = X_{\text{ms},m} + \text{rand} \cdot \left(\frac{\sum_{m=1}^{N_{\text{ms}}} X_{\text{ms},m} \cdot w_{\text{ms},m}}{\sum_{m=1}^{N_m} w_{\text{ms},m}} - X_{\text{ms},m} \right) \tag{20}$$

In Eq. (19), $\text{Vib}_{\text{fs,nearest}}$ is the vibration of female closest to being considered male m and is obtained by

$$\text{Vib}_{\text{fs,nearest}} = w_{\text{fs,nearest}} \cdot e^{-d^2_{m,\text{nearest}}} \tag{21}$$

where $w_{\text{fs,nearest}}$ is the weight of the female spider closest to being considered male m and $d_{m,\text{nearest}}$ is the distance between the closest female and male m.

The third generation (mating operation for giving birth to baby spiders) Mating operation is the action of leading

males and other females for maintaining spider community. The operation is corresponding to the third new solution generation in SSO method. Leading males move within their own controlled zone and carries out mating with females in the zone. The zone is a circle and its radius is obtained by

$$\text{Radius} = \frac{\sum_{i=1}^{D} \left(z_{i,\max} - z_{i,\min} \right)}{2 \cdot D} \quad (22)$$

where $z_{i,\min}$ and $z_{i,\max}$ are the upper and lower limitations of control variable z; D is the control variable dimension.

After restoring dominant males and females in the pre-determined circle, baby spiders will be given birth. The phenomenon is corresponding to the generation of new solutions but it is different from the first and the second generations because the third generation cannot be mathematically formulated. In fact, each new solution is produced by random selection of control variables in the position of such dominant male and females.

The whole search procedure of SSO method for solving a typical optimization is illustrated in Fig. 1.

4.2 Proposed algorithm

In the section, we suggest some modifications that should be performed on SSO for tackling several disadvantages of SSO such as (1) many control parameters needing selection of values such as the population N_{pop}, probability P_m and the highest iteration HI; (2) many computation steps such as calculation of vibration, weight and fitness function; (3) high oscillation and (4) low convergence to good quality solutions. Our modifications are as follows:

1. *Set the term* "rand(rand − 0.5)" *in Eqs.* (14) *and* (19) *to zero*. It is clear that value of "rand(rand − 0.5)" is randomly produced within the range [− 0.5; 0.5] and does have mutual relationship with old solutions, $X_{\text{fs},f}$ and $X_{\text{ms},m}$. Thus, the contribution of the term may be insignificant and even it can lead to worse result. In fact, for ORPD problem with IEEE 30-bus system and IEEE 118-bus system, optimal solutions contain different control variables such as voltage magnitude in per unit (PU) within the range of [0.95; 1.1], tap changer in (PU) within the range of [0.9; 1.1] and reactive power of VAR compensators within the range of [0; 5] for IEEE 30-bus system and [− 40; 20] for IEEE 118-bus system. It can be indicated that the term "rand(rand − 0.5)" with values from − 0.5 to 0.5 may not much influence reactive power of VAR compensators but its impact on voltage magnitude and tap changer is highly remarkable. As a result, optimal solutions will be negatively influenced by the random
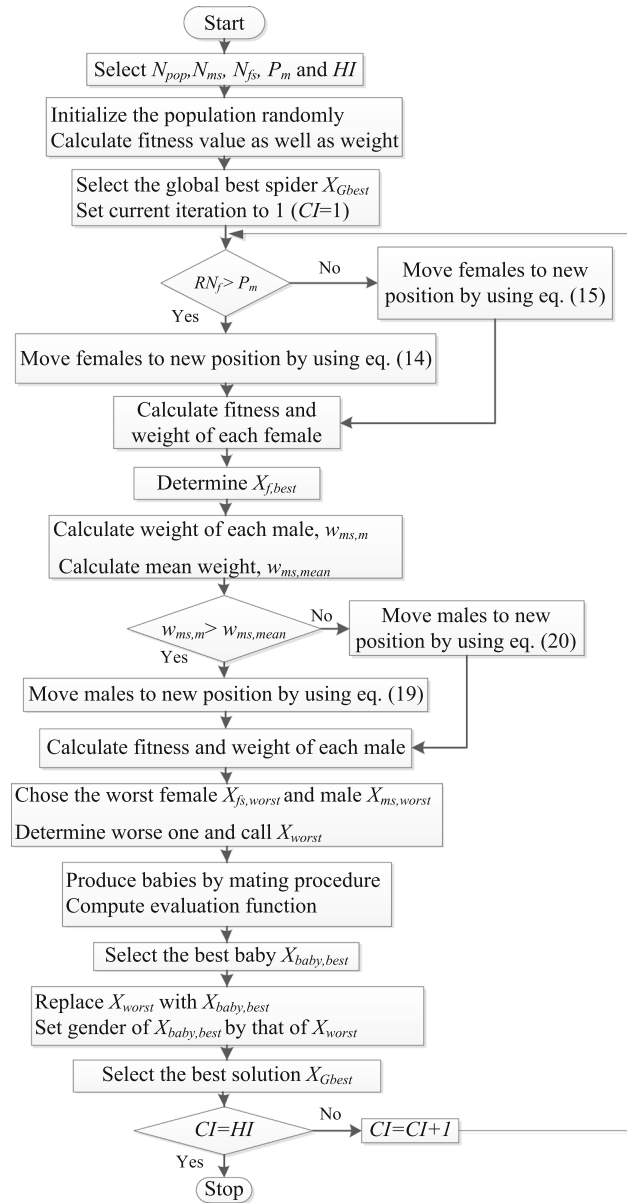

Fig. 1 The flowchart of using SSO for solving a typical optimization problem

terms in Eqs. (14) and (19), leading to failure for the optimization operation of transmission power system.

2. *Use only Eq.* (14) *for moving females*. In Eq. (14), $X_{\text{fs},f}$ is newly updated by adding two terms rand · Vib$_{\text{nearest}}$ · $(X_{\text{nearest}} - X_{\text{fs},f})$ and rand · Vib$_{\text{Gbest}}$ · $(X_{\text{Gbest}} - X_{\text{fs},f})$ to $X_{\text{fs},f}$ while in Eq. (15) $X_{\text{fs},f}$ is updated by subtracting the two terms from $X_{\text{fs},f}$. Clearly, the main difference between Eqs. (14) and (15) is the use of addition and subtraction, leading to different performance. As shown in [55], 70% of using Eq. (14) can result in better solutions for most benchmark functions. However, as thoroughly observed from formulas (20) and (21)

calculating velocity and position of PSO [17], formulas (15) and (23) producing new solutions of CSA via levy flights and strange egg discovery [81], formulas (1), (2) and (3) calculating frequency, new velocity and new position of bat algorithm [82] and formula (13) producing new solutions of DE [22], such methods have used addition instead of subtraction. The use of both addition and subtraction was applied only in [17] for PG-PSO and IPG-PSO but there had to be utilization condition for the two strategies dependent on their efficiency for the first iteration. If addition was more effective for the previous iteration, it would be used in the current iteration. Otherwise, subtraction would be selected for the considered iteration. By using the theory and constriction factor, the two methods in [17] could get better performance than other PSO methods including PSO methods with the combination of constriction factor and other improvements. The results could clearly advise that there must be a condition for the use of adding or subtracting a step size. Thus, in order to overlap the drawback of SSO method, we suggest using only Eq. (14) with slightly change as shown in Eq. (23) and cancel Eq. (15) for moving the position of female spiders corresponding to producing N_{fs} new solutions. The single use of Eq. (23) can cancel the selection of P_m, shorten computation time for determining optimal solutions and support the proposed method to be convergent to better optimal solutions.

$$X_{\text{fs},f} = X_{\text{fs},f} + \text{rand} \cdot \text{Vib}_{\text{nearest}} \cdot (X_{\text{nearest}} - X_{\text{fs},f}) + \text{rand} \\ \cdot \text{Vib}_{\text{Gbest}} \cdot (X_{\text{Gbest}} - X_{\text{fs},f})$$
(23)

3. *Use only Eq. (19) for moving males.* Observing from Eq. (20), we can see that new position of male spider is directly impacted by the weight of all males. Furthermore, the method is also completely different from all optimization algorithms. There have not been studies that indicate the combination of fitness function/weight and old solutions can lead to better solution as used in Eq. (20). Thus, the formula should be ignored for better performance. In addition, in Eq. (19), we also replace the female closet to the considered male with the best female, who has just been found after the movement of all females. For the modification, we can stop calculating the weight of all males, the mean weight of all males and stop determining the female closest to the considered male. As a result, the movement of all males is modeled as only one following equation.

$$X_{\text{ms},m} = X_{\text{ms},m} + \text{rand} \cdot \text{Vib}_{\text{fs,best}} \cdot (X_{\text{fs,best}} - X_{\text{ms},m})$$
(24)

where $\text{Vib}_{\text{fs,best}}$ and $X_{\text{fs,best}}$ are the vibration and the position of the best female, respectively.

The effectiveness and robustness of the use of Eqs. (23) and (24) will be tested and discussed in the numerical results.

The whole search process of solving a typical optimization problem by using the proposed method is clearly shown in Fig. 2. The observation from Figs. 1 and 2 can represent the simplicity of the proposed method and the superiority of the proposed method over SSO method. Namely, the points are as follows:

1. Reduction in one control parameter P_m and the comparison between RN_f and P_m: The task for tuning P_m is no longer necessary in the proposed method, leading to the cancelation of the comparison between RN_f and P_m. As a result, the computation steps and simulation time can be shortened.
2. Cancelation of Eqs. (15) and (20): This task not only reduces the computation steps but also gives more chances for producing promising solutions with high quality by using Eqs. (23) and (24).
3. No calculation of the weight of each male $w_{\text{ms},m}$ and mean weight $w_{\text{ms,mean}}$ for the whole males and the cancelation of the comparison between $w_{\text{ms},m}$ and $w_{\text{ms,mean}}$: Eq. (18) for determining the weight of each male is not used and the mean weight of the whole males is no longer needed in the proposed method, resulting in the reduction in the computation steps and shorter simulation time.

5 The application of the proposed method for solving ORPD problem

5.1 Initialization

In the considered ORPD problem, the position of male spiders and female spiders restores unknown variables playing important role such as voltage of generators, tap changer of transformers and MVAR of compensators. For better observation, such position is mathematically modeled by

$$X_s = \{V_{G1,s}, \ldots, V_{GN_G,s}, T_{1,s}, \ldots, T_{N_t,s}, Q_{c1,s}, \ldots, Q_{cN_c,s}\}^{\text{T}}; \\ s = 1, \ldots, N_{\text{pop}}$$
(25)

At the beginning, each position is randomly produced within upper and lower values as the following expression

$$X_s = X_{\min} + \text{rand} \cdot (X_{\max} - X_{\min}); \ s = 1, \ldots, N_{\text{pop}}$$
(26)

where $X_{\min}$ and $X_{\max}$ are representing minimum values and maximum values of control variables, respectively, shown in formula (25).
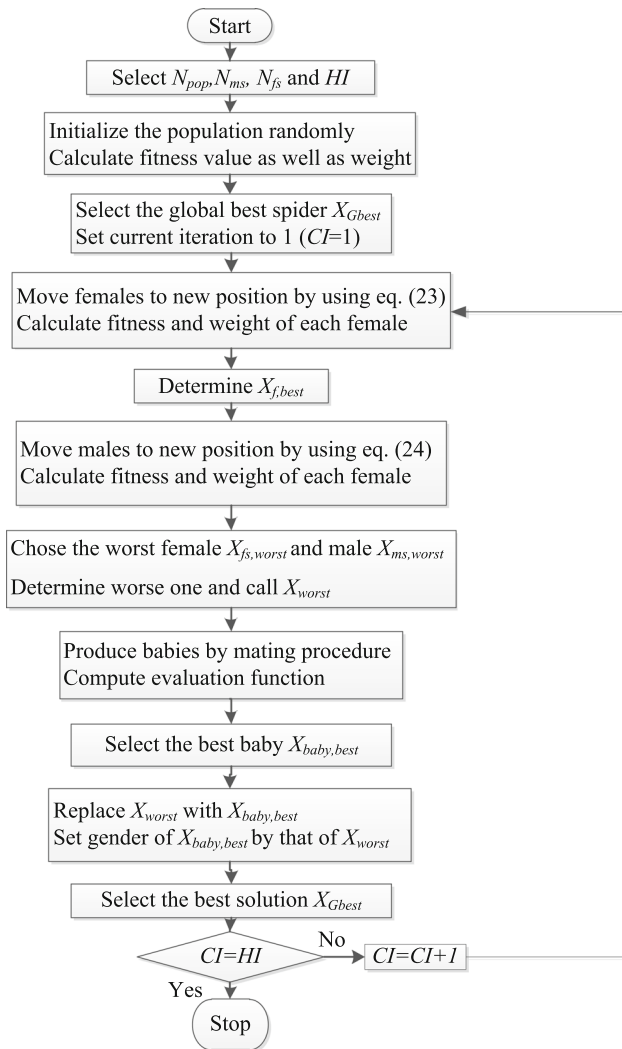
Fig. 2 The flowchart of using the proposed method for a typical optimization problem

After having enough number of control variables, reactive power of generators, voltage of load buses as well as apparent power flow of transmission lines are yielded by running MATPOWER 4.1 and fitness function evaluating quality of solutions is then constructed by present of objective and punishments of obtained variables from program of MAT-POWER 4.1. The fitness function is established as follows:

$$FF_s = \text{Objective} + \lambda_1 \left(\sum_{i=1}^{N_G} \Delta Q_{Gi} \right) + \lambda_2 \left(\sum_{i=1}^{N_{\text{load}}} \Delta V_{\text{load}i} \right) + \lambda_3 \left(\sum_{l=1}^{N_{\text{line}}} \Delta S_l \right)$$

(27)

where λ_1, λ_2 and λ_3 are amplification factors for punishment; ΔQ_{Gi}, $\Delta V_{\text{load}i}$ and ΔS_l are the punishment interval for violation of reactive power of generator i, voltage

magnitude of load bus i and apparent power flow of line l. λ_1, λ_2 and λ_3 are selected by experiment while ΔQ_{Gi}, $\Delta V_{\text{load}i}$ and ΔS_l are calculated by using the following formulas:

$$\Delta Q_{Gi} = \begin{cases} Q_{Gi} - Q_{Gi,\max} & \text{if } Q_{Gi} > Q_{Gi,\max} \\ Q_{Gi,\min} - Q_{Gi} & \text{if } Q_{Gi} < Q_{Gi,\min} \\ 0 & \text{else} \end{cases}$$

(28)

$$\Delta V_{\text{load}i} = \begin{cases} V_{\text{load}i} - V_{\text{load}i,\max} & \text{if } V_{\text{load}i} > V_{\text{load}i,\max} \\ V_{\text{load}i,\min} - V_{\text{load}i} & \text{if } V_{\text{load}i} < V_{\text{load}i,\min} \\ 0 & \text{else} \end{cases}$$

(29)

$$\Delta S_l = \begin{cases} S_l - S_{l,\max} & \text{if } S_l > S_{l,\max} \\ 0 & \text{else} \end{cases}$$

(30)

5.2 Stopping condition for iterative algorithm

The execution of ORPD based on the proposed method is an iterative algorithm that depends on a predetermined stopping condition. Most metaheuristic algorithms are using the highest iteration for stopping search process and in the paper, the proposed method is not also an exception. Thus, when the current iteration is equal to the highest iteration, which is predetermined, the search process can be terminated.

5.3 The whole computing procedure

The application of the proposed method for solving ORPD can be described in detail as follows:

Step 1:　Determine control parameters consisting of population size N_{pop}, the number of female spiders N_{fs}, the number of male spiders N_{ms} and the highest iteration HI

Step 2:　Randomly initialize the whole population using Eq. (26)

Step 3:　Run MATPOWER 4.1 program for determining reactive power of generators, voltage of load buses and apparent power flow of transmission lines

Step 4:　Evaluate solution quality by calculating Eq. (27)

- Set solution with the lowest fitness function to the global best solution X_{Gbest} and set current iteration to 1 (CI = 1).

Step 5:　Use Eq. (18) to calculate weight for whole spiders and calculate vibrations using Eqs. (16) and (17).

Step 6: Perform the first generation corresponding to moving females' position

- Check upper and lower boundaries: if solutions are higher upper bound, set them to upper bound (X_{max}) and if solutions are smaller than lower bound, set them to lower bound (X_{min}).
- Run MATPOWER 4.1 program for determining reactive power of generators, voltage of load buses and apparent power flow of transmission lines.
- Evaluate solution quality by calculating Eq. (27).
- Set solution with the lowest fitness to the best solution $X_{fs,best}$ and solution with the highest fitness to $X_{fs,worst}$.

Step 7: Perform the second generation corresponding to moving males' position.

- Check upper and lower boundaries: if solutions are higher upper bound, set them to upper bound (X_{max}) and if solutions are smaller than lower bound, set them to lower bound (X_{min}).
- Run MATPOWER 4.1 program for determining reactive power of generators, voltage of load buses and apparent power flow of transmission lines.
- Evaluate solution quality by calculating Eq. (27) and set solution with the highest to the worst solution $X_{ms,worst}$.

Step 8: Perform the third generation corresponding to mating operation

- Check upper and lower boundaries: if solutions are higher upper bound, set them to upper bound (X_{max}) and if solutions are smaller than lower bound, set them to lower bound (X_{min}).
- Run MATPOWER 4.1 program for determining reactive power of generators, voltage of load buses and apparent power flow of transmission lines.
- Evaluate solution quality by calculating Eq. (27).
- Set solution with the lowest fitness function to the best solution $X_{baby,best}$.
- Between $X_{fs,worst}$ and $X_{ms,worst}$, choose worse one and replace it with $X_{baby,best}$.

Step 9: Compare new position (new solution) with old position (old solution) of each spider to retain better one and abandon worse one.

Step 10: Determine the best solution among the current population X_{Gbest}.

Step 11: If CI = HI, stop computation procedure. Otherwise, back go step 4 and set CI = CI + 1.

6 Numerical results

In the section, we concentrate on comparison of results obtained by the proposed method and other existing methods in addition to other implemented methods such as (1) PSO [55]; (2) FA [57]; (3) CSA [58]; (4) FPA [59]; (5) SSA [78]; (6) MSSA [79]; (7) HSSSA [79]; (8) SSO [60]; (9) SSO with Eq. (23) (ISSO1); (10) SSO with Eq. (24) (ISSO2). Six benchmark functions and two standard systems, IEEE 30-bus system and IEEE 118-bus system, are used for running the methods. The platform and the computer for execution of the proposed method are, respectively, MATLAB 2016a and 2.4 Ghz processor with 4 Gb of ram. The whole information of the section is given in Table 3.

6.1 Impact analysis of proposed modifications on obtained results from benchmark functions

In the part, we run FA, CSA, PSO, FPA, SSA, MSSA, HSSSA, SSO, ISSO1, ISSO2 and the proposed method on six benchmark functions [83, 84] where 30 is selected as the number of variables. For simulation, we set N_{pop} to 50 for FA, PSO, FPA, SSA, MSSA and HSSSA but 30 for CSA, 40 for SSO, ISSO1, ISSO1 and ISSO while setting HI to 1,000 for all the methods. In addition, other parameters are also selected as follows:

1. FA: α = 0.25, 0.5, 0.75, 1.0
2. CSA: P_a = 0.2, 0.4, 0.6, 0.8, 1.0
3. PSO: $c_1 = c_2$ = 0.25, 0.5, 0.75, 1.0, 1.25, 1.5, 1.75, 2.0
4. FPA: P_a = 0.2, 0.4, 0.6, 0.8, 1.0
5. SSO and ISSO2: P_m = 0.7

The simulation results in terms of minimum and standard deviation of 50 independent trial runs for six benchmark functions are reported in Tables 4 and 5 for evaluating the best optimal solution quality and the stability of solution search among 50 runs of such compared methods. When the population size and the highest iteration are thoroughly selected for fair comparison of convergence speed, the quality of the best solution and the standard deviation, respectively, reflect the effectiveness and the robustness of compared methods. As given in Tables 4 and 5, the reported minimum and standard deviation of ISSO1 and ISSO2 are much less than those from

SSO but much higher than those from the proposed ISSO method for all functions. The indications can confirm the standout of ISSO1 and ISSO2 in terms of the effectiveness and the robustness over SSO. Clearly, using Eq. (23) is better than using both Eqs. (14) and (15), and using Eq. (24) is better than using both Eqs. (19) and (20). Furthermore, the combination of Eqs. (23) and (24) can lead to the best performance as seeing results achieved by ISSO. For comparisons with other methods such as PSO, FA, CSA, FPA, SSA, MSSA and HSSSA, the proposed ISSO method always reaches the best achievement with the best minimum and the best standard deviation but SSO is always worse than many methods in terms of minimum and standard deviation. In fact, SSO is worse than CSA for all functions in terms of both minimum and deviation. For comparison with FPA, SSO can find better result for only Rastrigin function. For comparison with state-of-the-art methods including SSA, MSSA and HSSA, SSO shows its shortcoming since its optimal solutions have higher minimum and standard deviation for most functions excluding Rastrigin function and Schwelfel_222 function.

In summary, we can conclude that the proposed modifications carried out on SSO reaches very good results and the proposed ISSO method is superior to popular metaheuristic algorithms including SSO, FA, CSA, FPA and PSO, and state-of-the-art methods consisting of SSA, MSSA and HSSA for benchmark functions.

6.2 Investigation of the proposed method's performance on IEEE 30-bus system

In the part, the proposed ISSO method is compared to FA, CSA, FPA, PSO, SSA, MSSA, HSSSA, SSO and other existing methods by implementing on IEEE 30-bus system. Such IEEE 30-bus system can be reached by referring to [85] and it consists of 6 generator buses, 24 load buses, 41 transmission lines, 9 VAR compensators and 4 transformers. The set of control variables included in position of spiders is comprised of voltage magnitude of 6 generators,

reactive power output of 9 VAR compensators and tap changer of 4 transformers. Fifty independent trial runs are performed for each method by setting HI to 50 for all methods and setting N_{pop} to 30 for PSO, FA, FPA, SSA, MSSA and HSSSA but setting to 20 for CSA and 25 for SSO and ISSO. The selection can balance the number of new produced solutions between ISSO and other methods as well as approximate computation time excluding FA, which must use high value for population. Other remaining control parameters of these methods are also set to the range shown in Sect. 6.1. Three single objectives including power loss, voltage deviation and L index are independently minimized in turn and the best results with respect to minimum, mean, maximum, standard deviation and computation time (CPU time) obtained by these methods and other methods are, respectively, summarized in Tables 6, 7 and 8. In addition, another important value, called improvement level (IL) in %, which is calculated by using Eq. (31) together with the TNFEs, is also reported in these tables.

$$\text{Improvement level } (\%)$$
$$= \frac{\text{min. of another method} - \text{min. of ISSO}}{\text{min. of another method}} 100\% \quad (31)$$

With respect to the value of IL, result with positive value (+) means the proposed method is better than others but result with negative value (−) indicates there is no improvement in the proposed method over others even the proposed method is less effective than such compared methods if other comparison criteria are accepted. Clearly, accurate comparison criteria need to be predetermined for assessing the effectiveness of compared methods. Thus, in the paper we consider the following factors as main accurate comparison criteria:

1. The comparison of minimum (or improvement level): aim to assess the best optimal solution quality.
2. The comparison of standard deviation: aim to assess the stability of optimal solution search ability.

Table 3 The description of study cases

Subsection	Implemented method	Test system	Objective function
6.1	FA, CSA, PSO, FPA, SSA, MSSA, HSSSA, SSO, ISSO1, ISSO2, the proposed method	Six benchmark functions	Minimize benchmark function
6.2	FA, CSA, PSO, FPA, SSA, MSSA, HSSSA, SSO, the proposed method	IEEE 30-bus system	Minimize:
			(1) Power loss
			(2) Voltage deviation
			(3) Voltage stability index
6.3	FA, CSA, PSO, FPA, SSA, MSSA, HSSSA, SSO, the proposed method	IEEE 118-bus system	Minimize:
			(1) Power loss
			(2) Voltage deviation
			(3) Voltage stability index

Table 4 Comparison of results obtained from Sphere, Rosenbrock and Rastrigin functions

Method	Sphere function		Rosenbrock function		Rastrigin function	
	Min	SD	Min	SD	Min	SD
PSO	7.86E+02	4.59E−13	3.69E+01	1.82E+02	1.73E−01	1.26E+01
FA	1.21E+02	1.70E+01	4.02E+03	1.00E+03	9.86E+01	2.12E+01
FPA	7.84E−05	1.06E−04	2.57E+01	4.66E−01	8.20E−05	1.26E−04
CSA	2.99E−12	9.44E−12	1.98E+01	5.64E−01	4.64E−13	1.83E−12
SSA	1.88E−01	8.44E−01	2.93E+01	8.05E+00	5.36E−02	1.86E−01
MSSA	3.60E−03	2.46E−01	2.60E+01	3.78E+01	9.57E−05	2.32E−02
HSSSA	3.75E−01	7.40E−01	2.71E+01	4.80E+00	2.53E−02	1.96E−01
SSO	4.05E+00	9.33E−01	2.64E+02	1.04E+02	4.91E−10	1.15E−05
ISSO1	6.1E−33	5.43E−9	3.93E−5	9.19E+00	2.21E−33	7.11E−10
ISSO2	4.92E−29	8.77E−10	5.57E−6	1.12E+01	5.35E−40	3.47E−11
ISSO	1.90E−53	1.66E−35	7.77E−17	5.29E+00	9.31E−128	6.89E−16

Table 5 Comparison of results obtained from Ackley, Griewangk and Schwelfel_222 functions

Method	Ackley function		Griewangk function		Schwelfel_222 function	
	Min	SD	Min	SD	Min	SD
PSO	2.02E+00	4.30E+00	3.36E+00	6.11E+00	8.81E+00	5.39E+00
FA	1.86E+01	3.37E−01	4.36E+02	5.52E+01	4.93E+04	7.79E+08
FPA	4.70E−02	1.23E−02	5.27E−04	3.84E−04	1.11E−01	9.01E−02
CSA	1.27E−05	5.13E−06	1.36E−11	3.76E−11	3.19E−05	2.23E−05
SSA	6.78E−01	7.12E−01	2.57E−01	8.29E−01	3.74E+00	2.47E+00
MSSA	4.85E−02	3.10E−01	2.93E−03	1.50E−01	3.69E+01	2.41E+01
HSSSA	8.69E−01	6.49E−01	1.20E−01	7.76E−01	3.22E+00	2.33E+00
SSO	1.71E+00	2.07E−01	1.13E−02	1.50E−01	2.07E−01	4.97E+00
ISSO1	1.08E−04	5.15E−04	6.25E−10	5.66E−06	8.47E−15	3.73E−09
ISSO2	5.71E−06	3.33E−05	1.09E−11	7.62E−07	1.93E−19	9.83E−15
ISSO	3.29E−14	1.07E−14	3.33E−16	0.00E+00	1.81E−60	3.35E−22

3. The comparison of the number of newly produced solutions to assess the solution search speed. In [86], authors have presented a convincing argument that population size and the iterations are two important factors in regard to the performance of implemented methods. Higher population size and iterations can improve found solution significantly but simulation time may be much longer. Thus, they have suggested that the number of fitness evaluations TNFEs (is also the total number of newly produced solutions) must be used for fairly evaluating applied methods. Namely, TNFEs can be calculated by the following formulas:

$$\text{TNFEs} = N_{\text{pop}} \cdot \text{HI} \tag{32}$$

$$\text{TNFEs} = 2 \cdot N_{\text{pop}} \cdot \text{HI} \tag{33}$$

$$\text{TNFEs} = \left(N_{\text{pop}} + N_{\text{bb}}\right) \cdot \text{HI} \tag{34}$$

Among the three formulas, Eq. (32) is applied for calculating TNFEs for the methods with one new solution generation per iteration such as PSO, FPA,

SSA and BBO, while Eq. (33) can find TNFEs for the methods with two new solution generations such as CSA, TLBO and QOTLBO. On the contrary, the SSO method and the proposed method are totally different because TNFEs in Eq. (34) are not a certain value for each run due to the uncertainty of N_{bb}, which is the number of babies produced per iteration. For reporting values of TNFEs for the SSO and the proposed methods, we have to count the total number of babies for the 50 runs and then the average value will be employed.

4. The verification of optimal solution accuracy: to assess the reliability of methods.

For power loss optimization case, the minimum power loss found by the proposed method to be 4.51445 MW and less than that of almost methods excluding GSA [32] with IL of − 0.003%, which is given in bold in Table 6. The accuracy of reported solution of GSA is checked and truly confirmed but the superiority of GSA over the proposed method is not accepted because GSA has produced 20,000

Table 6 Comparison of results obtained from IEEE 30-bus system with power loss optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
HPSO–TS [14]	4.5213	–	–	–	–	–	–		0.152
TS [14]	4.9203	–	–	–	–	–	–		8.248
PSO [14]	4.6862	–	–	–	–	–	–		3.665
SGA [30]	4.5692	–	–	–	–	300	60	18,000	1.2
PSO-TVIW [17]	4.84580	4.87610	5.22920	0.05620	8.76200	200	20	4000	6.838
PSO-TVAC [17]	4.84490	4.87020	4.96550	0.02630	8.68000	200	20	4000	6.821
SPSO-TVAC [17]	4.52620	4.55640	4.77160	0.05540	9.09200	200	20	4000	0.260
PSO-CF [17]	4.52580	4.57110	4.99900	0.08150	8.48000	200	20	4000	0.251
PG-PSO [17]	4.64250	4.73200	4.79720	0.11240	8.21600	200	20	4000	2.758
SWT-PSO [17]	4.65780	4.94130	5.25210	0.12210	7.99500	200	20	4000	3.078
PGSWT-PSO [17]	4.79140	5.23490	6.05120	0.21310	7.91200	200	20	4000	5.780
IPG-PSO [17]	4.52560	4.55080	4.94930	0.05920	7.85200	200	20	4000	0.246
DE [22]	4.55500	–	–	–	–	500	150	75,000	0.890
GSA [32]	4.51431	–	–	–	–	200	100	20,000	**− 0.003**
QOTLBO [38]	4.55940	4.56010	4.56170	0.03700	–	100	50	10,000	0.986
TLBO [38]	4.56290	4.56950	4.57480	0.05640	–	100	50	10,000	1.062
SGA [42]	4.94080	5.0378	5.1651	–	–	30,000	–	–	8.629
PSO [42]	4.9239	4.972	5.0576	–	–	30,000	–	–	8.316
HSA [42]	4.9059	4.924	4.9653	–	–	30,000	–	–	7.979
NMSFLA [54]	4.6118	4.61264	4.61749	0.00098	–	100	14	1400	2.111
ALO [50]	4.59000					100	–	–	1.646
JA [54]	4.62500	–	–	–	–	500	60	30,000	2.390
PSO	4.56787	4.99356	6.68261	0.49541	4.6	50	30	1500	1.169
FPA	4.62543	4.78287	5.07591	0.09795	4.8	50	30	1500	2.399
FA	5.22597	5.92571	6.97414	0.52432	134.1	50	30	1500	13.615
CSA	4.62388	4.73631	4.9388	0.06931	4.5	50	20	2000	2.367
SSA	4.71515	4.943208	5.71349	0.188697	5.1	50	30	1500	4.26
MSSA	5.001256	5.80103	6.947719	0.45394	5.2	50	30	1500	9.73
HSSSA	4.975122	5.410426	5.717224	0.166735	5.5	50	30	1500	9.26
SSO	4.86029	5.2259	5.5975	0.19162	4.7	50	25	≈ 1432	7.12
ISSO	4.51445	4.69215	4.52546	0.02799	4.5	50	25	≈ 1424	

new solutions and accomplished 20,000 fitness evaluations; meanwhile, the proposed method has updated and evaluated about 1424 new solutions. The vast work of GSA has indicated that GSA has used approximately 14 times the number of new solutions from the proposed method. As compared to other implemented methods such as PSO, FPA, FA, CSA, SSA, MSSA, HSSSA and SSO, the power loss yielded by the proposed method can result in a high improvement level, 1.169%, 2.399%, 13.615%, 2.367%, 4.26%, 9.73%, 9.26% and 7.116%, respectively. Furthermore, the proposed method has converged to better results with less number of new solutions and less number of fitness evaluations than these methods. These methods have produced and evaluated about 1500 and 2000 new solutions

while that from the proposed method was about 1424 new solutions. The comparison of the remaining methods shows that the proposed method can reach the improvement level approximately about 0.25 to 9%. The comparison of TNFEs can confirm fast search speed of the proposed method compared to other ones since TNFEs from other methods were from 4000 to 30,000. Clearly, the proposed method could be from 3.5 to 21 times faster than other ones. As a result, it can conclude that the proposed method is the most powerful optimization tool for the case because it reaches advantages such as the second best optimal solution, the fastest method, getting high improvement level compared to compared methods.

Table 7 Comparison of results obtained from IEEE 30-bus system with voltage deviation optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
PSO-TVIW [17]	0.1038	0.1597	0.5791	0.1112	12.25	200	20	4000	14.76
PSO-TVAC [17]	0.2064	0.2376	0.5796	0.0153	12.88	200	20	4000	57.14
SPSO-TVAC [17]	0.1354	0.1558	0.1833	0.0103	12.59	200	20	4000	34.66
PSO-CF [17]	0.1287	0.1557	0.4041	0.0404	12.94	200	20	4000	31.26
PG-PSO [17]	0.1202	0.1440	0.2593	0.0222	12.45	200	20	4000	26.40
SWT-PSO [17]	0.1614	0.1814	0.2296	0.1330	22.57	200	20	4000	45.19
PGSWT-PSO [17]	0.1539	0.2189	0.5532	0.0656	22.32	200	20	4000	42.51
IPG-PSO [17]	0.0892	0.1078	0.2518	0.0298	9.724	200	20	4000	0.82
DE [22]	0.0911	–	–	–	–	500	150	75,000	2.89
GSA [32]	**0.0676**	**–**	**–**	**–**	**–**	**200**	**100**	20,000	**− 30.87**
QOTLBO [38]	**0.0856**	**0.0872**	**0.0907**	**0.0314**	–	**100**	**50**	10,000	**− 3.35**
TLBO [38]	0.0913	0.0934	0.0988	0.0403	–	100	50	10,000	3.10
PSO	0.13203	0.4068	1.70393	0.28312	5.2	50	30	1500	32.99
FPA	0.14086	0.18363	0.22828	0.018	5.0	50	30	1500	37.19
FA	0.28811	0.66069	1.44986	0.36341	133.9	50	30	1500	69.29
CSA	0.12692	0.16432	0.2076	0.01655	4.3	50	20	2000	30.29
SSA	0.188411	0.374529	0.941759	0.166094	5.2	50	30	1500	53.04
MSSA	0.230087	0.690254	1.860037	0.333131	5.4	50	30	1500	61.55
HSSSA	0.174701	0.308337	0.576439	0.094216	5.6	50	30	1500	49.36
SSO	0.19304	0.2863	0.42681	0.05357	5.3	50	25	≈ 1386	54.17
ISSO	0.08847	0.11603	0.14938	0.02277	4.6	50	25	≈ 1375	

For the voltage magnitude deviation optimization case given in Table 7, it is surprised to see the bold values − 30.87% of GSA [32] and − 3.35% of QOTLBO [38], which imply that these methods are the two best optimization tools for the case of minimizing voltage magnitude. However, as we recheck by substituting reported solution to Mathpower, the minimum of GSA and QOTLBO is, respectively, 0.1862 and 0.1031, which are much higher than reported values 0.0676 and 0.0856. Based on the true values, IL is recalculated to be + 52.48% and + 14.19%. As compared to other remaining methods with valid solution or without solutions reported, the proposed method can reach very high improvement. For instance, the improvement can be up to 32.99%, 37.19%, 69.29%, 30.29%, 53.04%, 61.55%, 49.36%, 54.17% and 57.14% in comparison with PSO, FPA, FA, CSA, SSA, MSSA, HSSSA, SSO and PSO-TVAC, respectively. Similar to the previous case, the population size and the maximum iteration from the proposed method lead to the smallest work of generating and evaluating 1375 new solutions while the control parameters from other methods result in much higher work with from 1500 to 75,000 new solutions. The vast deviation separated the proposed method from other slow convergence methods and emphasized its outstanding performance. In summary, the proposed method reaches the best solution and gets the fastest search speed. Thus, it can confirm the real superiority of the proposed method over other ones for the case.

For comparison with other methods by considering voltage stabilization as an objective given in Table 7, the minimum and the improvement level of GSA [32] and ALO [50] are the two best results among all compared methods since they are, respectively, 0.1161 and − 7.37% while the minimum of the proposed method is 0.12466. However, recalculated minimum by substituting reported solution to Mathpower indicates that real values of GSA and ALO are, respectively, 0.1247 and 0.1241. IL is also recomputed to be + 0.03% and − 0.45%. Similarly, three other methods in [50] consisting of BA, GWO and ABC have also reported very good values of minimum such as 0.1191, 0.1180 and 0.1161 but the recalculated minimum values are, respectively, 0.1264, 0.1257 and 0.1264. QOTLBO [38] has also given an optimal solution with minimum of 0.1242 but dependent variable, reactive power of generator 4, is higher than upper limit. Namely, recalculated reactive power output is 79.1274 MVAR but upper limit is 60 MVAR. Clearly, many studies have reported wrong minimum and some of them have reported invalid solutions. On the contrary, IPG-PSO [17] and DE [22] have reported exact minimums, 0.1241 and 0.1246, which are

Table 8 Comparison of results obtained from IEEE 30-bus system with voltage stabilization index optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
PSO-TVIW [17]	0.1258	0.1270	0.1289	0.0008	14.42	200	20	4000	0.91
PSO-TVAC [17]	0.1499	0.1513	0.1544	0.0009	14.53	200	20	4000	16.84
SPSO-TVAC [17]	0.1271	0.1285	0.1297	0.0006	14.05	200	20	4000	1.92
PSO-CF [17]	0.1261	0.1279	0.1295	0.0008	14.39	200	20	4000	1.14
PG-PSO [17]	0.1264	0.1297	0.1313	0.0008	14.84	200	20	4000	1.38
SWT-PSO [17]	0.1488	0.1634	0.1806	0.0074	18.99	200	20	4000	16.22
PGSWT-PSO [17]	0.1394	0.1537	0.1749	0.0081	19.107	200	20	4000	10.57
IPG-PSO [17]	**0.1241**	**0.1266**	**0.1298**	**0.0010**	**13.75**	**200**	**20**	4000	**− 0.45**
DE [22]	**0.1246**						500	50	25,000	**− 0.05**
GSA [32]	**0.1161**	**–**	**–**	**–**	**–**	**200**	**100**	20,000	**− 7.37**
QOTLBO [38]	**0.1242**	**0.1245**	**0.1247**	**0.0452**	**–**	**100**	**50**	10,000	**− 0.37**
TLBO [38]	0.1252	0.1254	0.1258	0.0454	–	100	50	10,000	0.43
BA [50]	**0.1191**				94.65	**100**	**40**	4000	**− 4.67**
GWO [50]	**0.1180**				104.29	**100**	**40**	4000	**− 5.64**
ABC [50]	**0.1161**				105.04	**100**	**40**	8000	**− 7.37**
ALO [50]	**0.1161**	**–**	**–**	**–**	97.92	**100**	**40**	4000	**− 7.37**
PSO	0.12531	0.13265	0.15295	0.0082	4.8	50	30	1500	0.52
FPA	0.12556	0.12715	0.12918	0.00066	5.1	50	30	1500	0.72
FA	0.13813	0.15506	0.28362	0.03359	181	50	30	1500	9.75
CSA	0.12466	0.12659	0.12784	0.0018	6.7	50	20	1000	0.00
SSA	0.126595	0.141856	0.152356	0.005707	5.1	50	30	1500	1.53
MSSA	0.127679	0.151029	0.374735	0.035933	5.5	50	30	1500	2.36
HSSSA	0.131915	0.296015	4.916918	0.766127	5.8	50	30	1500	5.5
SSO	0.12738	0.13375	0.14455	0.00384	5.6	50	25	≈ 1388	2.14
ISSO	0.12466	0.12529	0.12706	0.0004	4.9	50	25	≈ 1382	–

better than result of the proposed method and result in improvement level − 0.45% and − 0.05%. Nevertheless, the two methods have used high values TNFEs, 4000 for IPG-PSO and 25,000 for DE while that of the proposed method has been 1382. Thus, we increase N_{pop} and HI to 20 and 150, 25 and 150, and 20 and 200, and results obtained are, respectively, given in Table 9. As observed minimum values given in the table, the proposed method can find better optimal solutions, which has minimum of 0.12425 at $N_{pop} = 25$ and HI = 150. Clearly, 0.12425 is better than 0.1246 of DE but it is not better than 0.1241 of IPG-PSO. Thus, the proposed method is not superior to IPG-PSO for the case of voltage stability index. In comparison with other remaining methods, the proposed method can find better optimal solution since it can reach the improvement level from 0.52 (compared to PSO) to 16.84% (compared to PSO-TVAC [17]). Furthermore, the proposed method has faster convergence speed than these methods since the proposed method has used the smallest value for TNFEs 1382 but that from other methods has been from 1500 to 25,000. In summary, the result comparison analysis for the

voltage stability optimization can result in a conclusion that the proposed method outperforms most methods in terms of better optimal solution and faster convergence speed excluding comparison with IPG-PSO [17].
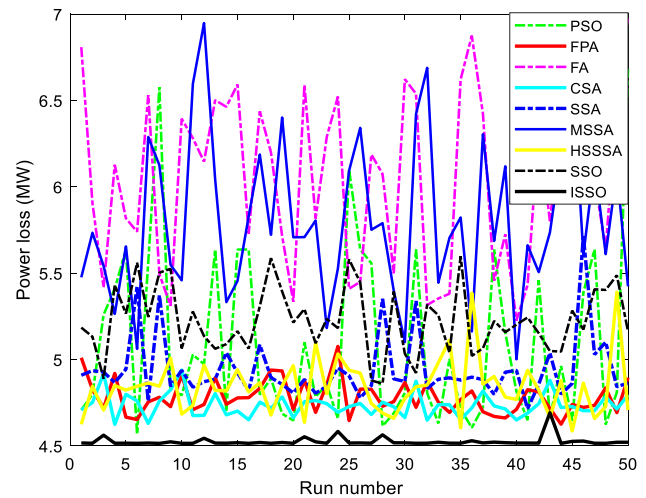
The best result of 50 independent runs obtained by nine implemented methods consisting of PSO, FA, CSA, FPA, SSA, MSSA, HSSSA, SSO and the proposed method for the optimization of three objectives is plotted in Figs. 3, 4 and 5. The figures let us know that FA, PSO, SSO and MSSA are four methods with the highest fluctuation, most solutions with low quality and the highest standard deviation while five remaining methods including FPA, CSA, SSA, HSSSA and the proposed method have low oscillation and more effective solutions. In particular, all values of the proposed method for three different objectives seem to be on a line and approximately all solutions of the proposed method are better than those of other ones. Solutions of the proposed method for the system are given in "Appendix".

6.3 Investigation of the proposed method's performance on IEEE 118-bus system
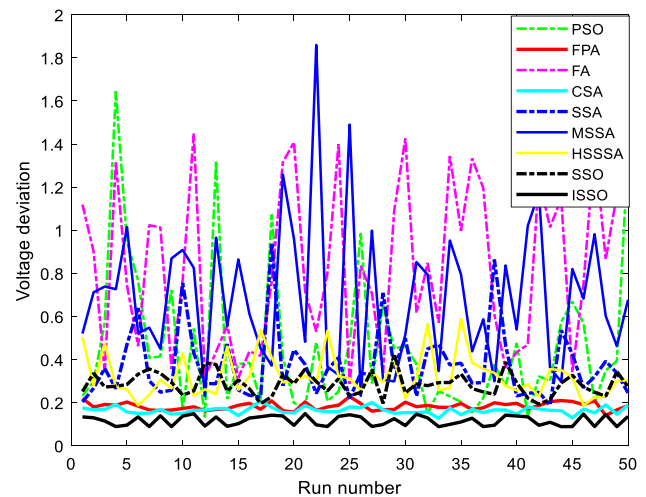
Similar to Sect. 6.2, in the part the performance of the proposed ISSO method continues to be investigated by comparing to CSA, FPA, PSO, SSO (in which FA cannot deal with the large system and obtain valid solutions) and other existing methods available in previous studies once IEEE 118-bus system is considered as a test. Readers can reach the whole data of such IEEE 118-bus system by referring to [85]. The system consists of 54 generator buses, 64 load buses, 186 transmission lines, 14 VAR compensators and 9 transformers. The set of control variables included in position of spiders is comprised of voltage magnitude of 54 generators, reactive power output of 14 VAR compensators and tap changer of 9 transformers. For implementation of the proposed method and other methods, HI is set to 150 while N_{pop} is not set to the same value for all methods such as $N_{pop} = 50$ for PSO, FPA, SSA, MSSA and HSSSA but $N_{pop} = 30$ for CSA and $N_{pop} = 40$ for SSO and the proposed method. Results with respect to minimum, average, maximum and standard deviation obtained by such eight implemented methods and other methods are reported in Table 10 for power loss minimization, in Table 11 for voltage magnitude deviation minimization and in Table 12 for L index minimization. Besides, improvement level, computation time on average for each run, control parameters, N_{pop} and HI, and TNFEs are also summarized in the tables for better comparison. The improvement level given in such tables can imply the proposed method can search better optimal solutions than most methods and the improvement level can be up to 13.29% compared to PSO [13] for power loss minimization, 92.75% compared to PSO [13] for voltage deviation minimization and 37.1% compared to CLPSO [13] and 56.27% compared to PSO [13] for L index minimization. In addition, the improvement level compared to PSO, FPA, CSA, SSA, MSSA, HSSSA and SSO is, respectively, 6.63%, 11.66%, 5.56%, 8.98%, 7.70%, 9.61% and 36.08% for power loss objective, 27.49%, 60.16%, 72.90%, 64.41%, 64.95%, 61.10% and 47.91% for voltage deviation
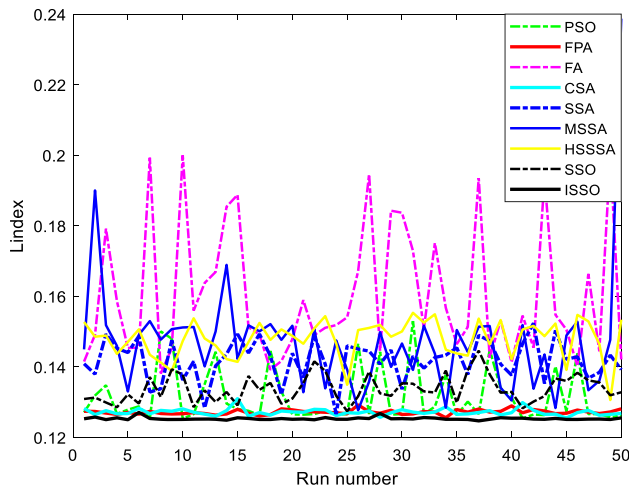

Fig. 3 Power loss of 50 runs obtained by compared methods for IEEE 30-bus system

Fig. 4 Voltage deviation of 50 runs obtained by compared methods for IEEE 30-bus system

objective and 0.16%, 1.30%, 0.16%, 3.13%, 4.30%, 3.35% and 13.29% for L index objective. On the other hand, these implemented methods have been assigned by high enough values of N_{pop} and HI, so they have used more new solutions and more fitness evaluations from 7500 to 9000 but that of the proposed method was less than 7500. The comparison of improvement level and TNFEs can identify high-quality search process of the proposed over these compared methods.

For the three cases of optimization, Figs. 6, 7 and 8 show fitness function of 50 runs obtained by PSO, FPA, CSA, SSA, MSSA, HSSA and ISSO but there is no result for SSO in the figures because most runs of SSO obtain high fitness values, leading to a unclear sight for clear comparison. Observing these figures can indicate that the

Table 9 Different results obtained by the proposed method by setting different values to N_{pop} and HI

N_{pop}	20	25	20
HI	**150**	**150**	**200**
Min	0.12460	0.12425	0.12447
Avg.	0.12553	0.12475	0.12540
Max	0.12709	0.12612	0.12689
SD	0.00075	0.00038	0.00061
CPU time (s)	10.51375	13.77134	14.43990

Fig. 5 L index of 50 runs obtained by compared methods for IEEE 30-bus system

proposed method has better solution search stabilization since its values have a small deviation with low oscillation but those of others have very high fluctuations. Clearly, the improvement is significant. However, there are limitations that the proposed method cannot be more effective than SARGA [28] and QOTLBO [38] for power loss

minimization, IPG-PSO [17] for voltage deviation minimization and PSO-TVIW [17], SWT-PSO [17] and PGSWT-PSO [17] for L index minimization. Namely, the improvement level of the proposed method superior to such methods is − 1.25% (SARGA) and − 2% (QOTLBO), − 0.12% (IPG-PSO) for voltage deviation minimization and L index minimization and − 0.17% (PSO-TVIW), − 3.41% (SWT-PSO), − 5.75% (PGSWT-PSO) and − 6,87% (IPG-PSO) for L index minimization. As checked optimal solution, we found that SARGA has not reported optimal solution. Clearly, the proposed method has better results than QOTLBO [38] for two cases, optimization of voltage deviation and optimization of L index but its results are worse than those of QOTLBO [38] for power loss optimization. As compared to PSO-TVIW [17], SWT-PSO [17] and PGSWT-PSO [17], the proposed method also reaches better results for two cases, optimization of power loss and optimization of voltage deviation but its results are worse than these methods for L index. Compared to IPG-PSO, the proposed method has better result for only one case, optimization of power loss but for two other cases, the proposed method cannot reach better results. However, IPG-PSO has been controlled by assigning to higher HI, 200 but that of the proposed method is only 150. Thus, we

Table 10 Comparison of results obtained from IEEE 118-bus system with power loss optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
CLPSO [13]	130.96	–	–	–	–	200	120	24,000	12.55
PSO [13]	131.99	–	–	–	–	200	120	24,000	13.23
PSO-TVIW [17]	116.8976	118.2344	126.6222	1.6009	109.645	200	40	8000	2.03
PSO-TVAC [17]	124.3335	129.7494	134.1254	2.156	96.32	200	40	8000	7.89
SPSO-TVAC [17]	116.2026	117.3553	118.139	0.4696	96.45	200	40	8000	1.44
PSO-CF [17]	115.6469	116.9863	119.8378	0.8655	95.86	200	40	8000	0.97
PG-PSO [17]	116.6075	119.3968	127.0772	2.107	96.11	200	40	8000	1.78
SWT-PSO [17]	124.1476	129.371	141.6147	3.309	91.58	200	40	8000	7.75
PGSWT-PSO [17]	119.427	122.781	125.762	1.2455	95.17	200	40	8000	4.10
IPG-PSO [17]	115.06	116.462	118.35	0.528	91.07	200	40	8000	0.46
SARCGA [28]	**113.12**	**113.968**	–	**0.0002**	–	**300**	**15**	9000	**− 1.25**
HEP [28]	115.58	115.8	–	0.0018	–	**300**	**15**	4500	0.91
QOTLBO [38]	**112.2789**	**113.7693**	**115.4516**	**0.0244**	–	**100**	**50**	10,000	**− 2.00**
TLBO [38]	116.4003	121.3902	118.4427	0.0482	–	100	50	10,000	1.61
PSO	122.6579	126.3469	133.1325	2.1915	40.8	150	50	7500	6.63
FPA	129.6524	138.4028	147.7131	4.0914	45.3	150	50	7500	11.66
CSA	121.2732	124.1214	126.7648	1.2447	50.9	150	30	9000	5.56
SSA	125.8324	129.1417	132.5658	1.555358	41.4	150	50	7500	8.98
MSSA	124.0818	133.2492	151.8367	4.875804	42.6	150	50	7500	7.7
HSSSA	126.6992	129.3808	133.7336	1.589492	43.2	150	50	7500	9.61
SSO	179.1816	312.9189	756.2027	123.282	43.3	150	40	≈ 7246	36.08
ISSO	114.5297	115.651	121.1127	1.4889	41.6	150	40	≈ 7190	–

Table 11 Comparison of results obtained from IEEE 118-bus system with voltage deviation optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
CLPSO [13]	1.6177	–	–	–	–	200	120	24,000	89.97
PSO [13]	2.2359	–	–	–	–	200	120	24,000	92.75
PSO-TVIW [17]	0.1935	0.2291	0.2809	0.0206	78.49	200	40	8000	16.18
PSO-TVAC [17]	0.3921	0.4724	0.5407	0.0316	78.7	200	40	8000	58.63
SPSO-TVAC [17]	0.2074	0.2498	0.3012	0.0215	74.9	200	40	8000	21.79
PSO-CF [17]	0.1801	0.2143	0.3384	0.0286	78.13	200	40	8000	9.94
PG-PSO [17]	0.1658	0.2084	0.2354	0.021	51.24	200	40	8000	2.17
SWT-PSO [17]	0.1658	0.2084	0.2354	0.021	51.24	200	40	8000	2.17
PGSWT-PSO [17]	0.2355	0.2755	0.3239	0.0205	114.5	200	40	8000	31.13
IPG-PSO [17]	**0.162**	**0.1923**	**0.2147**	**0.0184**	**47.86**	**200**	**40**	**8000**	**− 0.12**
QOTLBO [38]	0.191	0.2043	0.2267	0.0356	–	100	50	10,000	15.08
TLBO [38]	0.2237	0.2306	0.2543	0.0384	–	100	50	10,000	27.49
PSO	0.4071	0.4975	0.6834	0.0612	41.6	150	50	7500	60.16
FPA	0.5986	0.7253	0.9273	0.0751	46.8	150	50	7500	72.90
CSA	0.3114	0.3672	0.438	0.032	52.6	150	30	9000	47.91
SSA	0.455703	0.533246	0.678477	0.05021	42.6	150	50	7500	64.41
MSSA	0.462826	0.620333	1.092311	0.136598	43.6	150	50	7500	64.95
HSSSA	0.416974	0.542517	0.625822	0.044202	44.2	150	50	7500	61.1
SSO	1.1588	1.451	1.668	0.254	44.3	150	40	≈ 6883	86
ISSO	0.1622	0.1894	0.6201	0.0733	42.4	150	40	≈ 6825	–

Table 12 Comparison of results obtained from IEEE 118-bus system with voltage stabilization index optimization

Method	Min	Avg.	Max	SD	CPU time (s)	HI	N_{pop}	TNFEs	IL (%)
CLPSO [13]	0.0965	–	–	–	–	200	120	24,000	37.10
PSO [13]	0.1388	–	–	–	–	200	120	24,000	56.27
PSO-TVIW [17]	**0.0606**	**0.0607**	**0.0612**	**0.0001**	**119.66**	**200**	**40**	**8000**	**− 0.17**
PSO-TVAC [17]	0.0607	0.0609	0.0613	0.0001	119.22	200	40	8000	0.00
SPSO-TVAC [17]	0.0607	0.0608	0.0612	0.0001	119.16	200	40	8000	0.00
PSO-CF [17]	0.0606	0.0607	0.061	0.0001	119.86	200	40	8000	− 0.17
PG-PSO [17]	0.0654	0.0656	0.0721	0.0002	119.65	200	40	8000	7.19
SWT-PSO [17]	**0.0587**	**0.0608**	**0.0641**	**0.0012**	**58.45**	**200**	**40**	**8000**	**− 3.41**
PGSWT-PSO [17]	**0.0574**	**0.0605**	**0.0683**	**0.0018**	**56.43**	**200**	**40**	**8000**	**− 5.75**
IPG-PSO [17]	**0.0568**	**0.0569**	**0.0583**	**0.0002**	**55.62**	**200**	**40**	**8000**	**− 6.87**
QOTLBO [38]	0.0608	0.0631	0.0616	0.0476	–	100	50	10,000	0.16
TLBO [38]	0.0613	0.0626	0.0646	0.0488	–	100	50	10,000	0.98
PSO	0.0608	0.0615	0.0656	9.03E−04	43.1	150	50	7500	0.16
FPA	0.0615	0.0629	0.0652	8.49E−04	48.6	150	50	7500	1.30
CSA	0.0608	0.0611	0.0619	2.34E−04	56.7	150	30	4500	0.16
SSA	0.062661	0.064864	0.066953	0.001028	45	150	50	7500	3.13
MSSA	0.063429	0.065875	0.068974	0.001415	46.9	150	50	7500	4.3
HSSSA	0.062804	0.064917	0.066953	0.000851	48.1	150	50	7500	3.35
SSO	0.07	85.9729	411.7652	100.0974	48.5	150	40	≈ 6821	13.29
ISSO	0.0607	0.0608	0.061	5.59E−05	45.2	150	40	≈ 6614	–

try the proposed method's performance by setting HI to 200 and fixing $N_{pop} = 40$. Results obtained given in Table 13 show that power loss and voltage deviation are 114.296 MW and 0.15541, respectively, which reach the improvement level over IPG-PSO to be 0.664% and 4.07% but L index of the proposed method is still worse than that of IPG-PSO with the improvement level of − 6.8%.

In short, the search performance of the proposed method has been further investigated by simulating results on the large-scale system with 118 buses and three single objective functions. The evaluation conclusion is done based on three comparison criteria such as (1) the best optimal solution judged via minimum objective function and improvement level, (2) optimum solution search speed judged via TNFEs and (3) the search stabilization judged via 50 runs. The three main points have been clarified and resulted in a conclusion that the proposed method is significantly superior to other implemented methods consisting of FA, PSO, CSA, FPA, SSA, MSSA, HSSSA and SSO. The comparison with other methods available in other studies also indicates that the proposed method can be more effective than all methods excluding IPG-PSO for L index optimization case only. Consequently, the proposed method is a very effective method for IEEE 118-bus system of ORPD problem. The optimal solutions obtained by the proposed method are given in "Appendix".

7 Conclusion

This paper has implemented a social spider optimization algorithm for solving the ORPD problem considering three independent objectives including power loss minimization, voltage deviation minimization and voltage stabilization
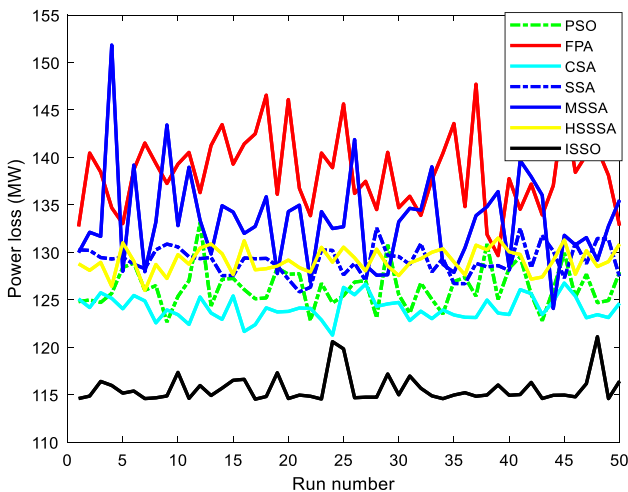

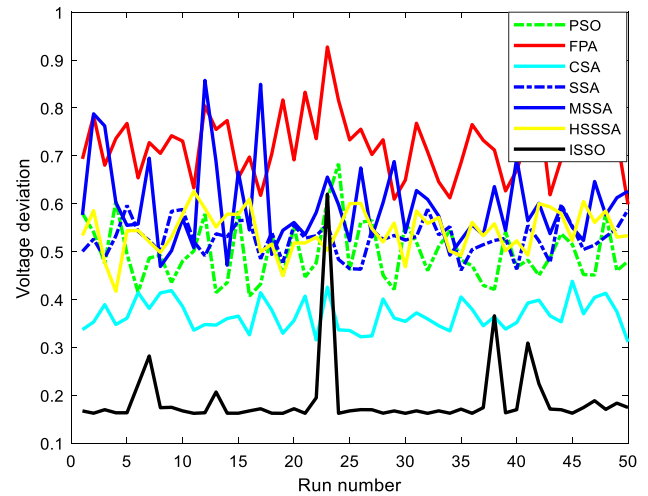**Fig. 6** Power loss of 50 runs obtained by compared methods for IEEE 118-bus system

Fig. 7 Voltage deviation of 50 runs obtained by compared methods for IEEE 118-bus system
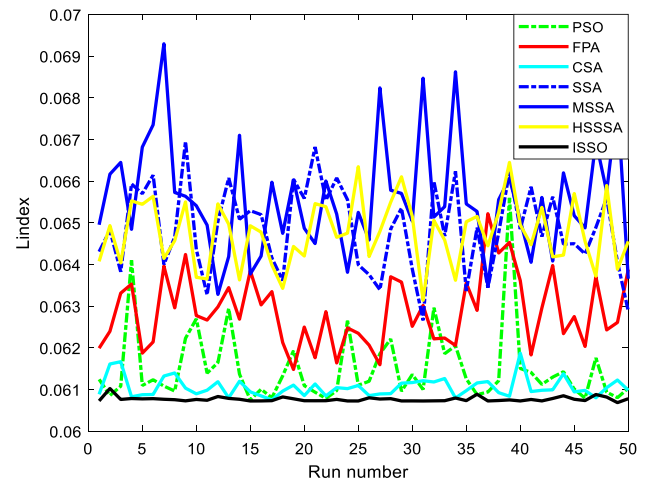

Fig. 8 L index of 50 runs obtained by compared methods for IEEE 118-bus system

enhancement. The proposed method is an improved metaheuristic algorithm by implementing modifications on two procedures of the new solution generation of the conventional social spider optimization algorithm. In the conventional SSO, there are two different formulas to be used for each generation and there must be conditions for a decision which formula to be used. Therefore, the

Table 13 Results obtained by the proposed method and setting $N_{pop} = 40$ and HI = 200 for IEEE 118-bus system

Objective	Min	Avg.	Max	SD	CPU time (s)
Power loss	114.296	114.553	121.244	0.829	55.7
VD	0.15541	0.16265	0.36537	0.024	59.1
L index	0.06069	0.06073	0.06112	5.7E−05	60.5

computation and comparison are carried out many times in the conventional SSO method. In the two generations of the improved method, only one formula with the changes is used for producing new solutions while the other one is ignored. Consequently, as compared to that of the standard SSO method, the implementation of proposed method for solving a typical optimization problem as well as benchmark optimization functions and different systems of ORPD problem is simplified significantly thank to the following advantages: 1) control parameter P_m has been canceled, reducing the task of tuning the most appropriate values and comparison between random number RN_f and P_m; (2) determination of new positions for females and male spider has become less complicated since Eqs. (15) and (20) have been discarded due to low effectiveness; (3) calculation of weight for each male and mean weight for all males and the comparison between individual weight and mean weight are no longer necessary. By possessing these advantages, the proposed method could find better solutions with lower fitness function and faster computational time to the proposed method while the conventional SSO is coping with drawbacks such as the complicated computation, many comparison conditions, long time for tuning control parameters and low convergence speed to high-quality solutions. The proposed method together with the conventional SSO and other methods has been implemented for solving benchmark functions without complicated constraints and two standard IEEE power systems with 30 buses and 118 buses considering a set of equality and inequality constraints. The results obtained by the proposed method have been verified by comparing to those

from other methods available in previously published studies. The comparisons of the objective values and calculation speed have indicated that the proposed method has outperformed SSO, PSO, FA, FPA, CSA, SSA, MSSA and HSSSA methods for all studied cases and the most compared methods reported in other studies. Moreover, the performance of the proposed method is also effective and robust because it can find better solutions with faster computational time for most study cases. Therefore, the proposed method can be one of the powerful optimization tools for dealing with the ORPD problem. For future work, we will try the performance of the proposed method for solving a new ORPD problem with the presence of wind turbines and distributed generators in aim to reduce energy loss and enhance stable operation of power systems. In the new work, the proposed method is in charge of determining the location and the capacity of wind turbines and distributed generators. The obtained results are evaluated via the energy loss and the operation stability of power systems.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Tables 14, 15, 16 and 17.

Table 14 Optimal solutions obtained by the proposed method for Case 3

Input/control variables	Minimize power loss	Minimize Vol. dev.	Minimize L index
P_{G1} (MW)	97.9257	99.1329	98.3034
P_{G2}	80	80	80
P_{G5}	50	50	50
P_{G8}	20	20	20
P_{G11}	20	20	20
P_{G13}	20	20	20
V_{G1} (pu)	1.1	1.011	1.0921
V_{G2}	1.0939	1.0067	1.0903
V_{G5}	1.0744	1.0182	1.0983
V_{G8}	1.0762	1.0057	1.0747
V_{G11}	1.0993	1.031	1.0964
V_{G13}	1.0999	1.0122	1.0992
Q_{C10} (MVAR)	4.8421	4.9133	3.8967
Q_{C12}	4.9287	4.1121	3.9619
Q_{C15}	4.6199	4.9917	1.8803
Q_{C17}	4.8338	0.0067	1.565
Q_{C20}	4.1948	5	3.3746
Q_{C21}	4.9951	4.9936	0.3977

Table 14 (continued)

Input/control variables	Minimize power loss	Minimize Vol. dev.	Minimize L index
Q_{C23}	2.4763	5	0.3323
Q_{C24}	4.9517	5	0.2433
Q_{C29}	2.2404	2.628	0.3239
T_{11}	1.0397	1.047	0.9637
T_{12}	0.9011	0.9	0.9114
T_{15}	0.9782	0.9908	0.9575
T_{36}	0.9652	0.9678	0.9415

Table 15 Optimal solution obtained by ISSO for the IEEE 118-bus power system with minimization of power loss

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G1} (MW)	0	P_{G100}	252	V_{G77}	1.051
P_{G4}	0	P_{G103}	40	V_{G80}	1.0615
P_{G6}	0	P_{G104}	0	V_{G85}	1.0486
P_{G8}	0	P_{G105}	0	V_{G87}	1.0478
P_{G10}	450	P_{G107}	0	V_{G89}	1.0654
P_{G12}	85	P_{G110}	0	V_{G90}	1.047
P_{G15}	0	P_{G111}	36	V_{G91}	1.0494
P_{G18}	0	P_{G113}	0	V_{G92}	1.0563
P_{G19}	0	P_{G116}	0	V_{G99}	1.0477
P_{G24}	0	V_{G1} (pu)	1.0291	V_{G100}	1.0508
P_{G25}	220	V_{G4}	1.0478	V_{G103}	1.04
P_{G26}	314	V_{G6}	1.0401	V_{G104}	1.03
P_{G27}	0	V_{G8}	1.0387	V_{G105}	1.0255
P_{G31}	7	V_{G10}	1.0393	V_{G107}	1.0117
P_{G32}	0	V_{G12}	1.0369	V_{G110}	1.0186
P_{G34}	0	V_{G15}	1.0333	V_{G111}	1.0264
P_{G36}	0	V_{G18}	1.0353	V_{G112}	1.0015
P_{G40}	0	V_{G19}	1.0325	V_{G113}	1.0419
P_{G42}	0	V_{G24}	1.0437	V_{G116}	1.05
P_{G46}	19	V_{G25}	1.0776	Q_{C5} (MVAR)	21.7236
P_{G49}	204	V_{G26}	1.0901	Q_{C34}	9.9396
P_{G54}	48	V_{G27}	1.0398	Q_{C37}	− 3.724
P_{G55}	0	V_{G31}	1.0304	Q_{C44}	9.7973
P_{G56}	0	V_{G32}	1.0349	Q_{C45}	9.9792
P_{G59}	155	V_{G34}	1.0455	Q_{C46}	4.5163
P_{G61}	160	V_{G36}	1.0435	Q_{C48}	7.5304
P_{G62}	0	V_{G40}	1.0255	Q_{C74}	7.878
P_{G65}	391	V_{G42}	1.0288	Q_{C79}	19.0955
P_{G66}	392	V_{G46}	1.0392	Q_{C82}	19.8919
P_{G69}	497.6133	V_{G49}	1.0545	Q_{C83}	9.9977
P_{G70}	0	V_{G54}	1.0275	Q_{C105}	13.6283
P_{G72}	0	V_{G55}	1.0261	Q_{C107}	1.92
P_{G73}	0	V_{G56}	1.0266	Q_{C110}	4.6279
P_{G74}	0	V_{G59}	1.0442	T_8 (pu)	0.9773
P_{G76}	0	V_{G61}	1.0437	T_{32}	1.0999
P_{G77}	0	V_{G62}	1.0429	T_{36}	0.9789

Table 15 (continued)

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G80}	477	V_{G65}	1.0577	T_{51}	0.977
P_{G85}	0	V_{G66}	1.0672	T_{93}	0.9924
P_{G87}	4	V_{G69}	1.0766	T_{95}	1.0015
P_{G89}	607	V_{G70}	1.047	T_{102}	0.9324
P_{G90}	0	V_{G72}	1.0419	T_{107}	0.9324
P_{G91}	0	V_{G73}	1.0447	T_{127}	0.9741
P_{G92}	0	V_{G74}	1.0367	P_{loss} (MW)	**114.5297**
P_{G99}	0	V_{G76}	1.0316		

Table 16 Optimal solution obtained by ISSO for the IEEE 118-bus power system with minimization of voltage deviation

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G1} (MW)	0	P_{G100}	252	V_{G77}	1.0103
P_{G4}	0	P_{G103}	40	V_{G80}	1.0155
P_{G6}	0	P_{G104}	0	V_{G85}	1.0199
P_{G8}	0	P_{G105}	0	V_{G87}	0.9912
P_{G10}	450	P_{G107}	0	V_{G89}	1.0018
P_{G12}	85	P_{G110}	0	V_{G90}	1.0215
P_{G15}	0	P_{G111}	36	V_{G91}	1.094
P_{G18}	0	P_{G113}	0	V_{G92}	1.0001
P_{G19}	0	P_{G116}	0	V_{G99}	0.9507
P_{G24}	0	V_{G1} (pu)	1.0036	V_{G100}	1.0359
P_{G25}	220	V_{G4}	1.0027	V_{G103}	1.1
P_{G26}	314	V_{G6}	0.9942	V_{G104}	1.1
P_{G27}	0	V_{G8}	1.012	V_{G105}	0.999
P_{G31}	7	V_{G10}	0.9698	V_{G107}	1.021
P_{G32}	0	V_{G12}	1.0113	V_{G110}	1.0051
P_{G34}	0	V_{G15}	1.0039	V_{G111}	1.0994
P_{G36}	0	V_{G18}	0.9917	V_{G112}	1.0998
P_{G40}	0	V_{G19}	1.0358	V_{G113}	0.9617
P_{G42}	0	V_{G24}	0.9814	V_{G116}	1.0033
P_{G46}	19	V_{G25}	1.0295	Q_{C5} (MVAR)	− 24.8638
P_{G49}	204	V_{G26}	1.0209	Q_{C34}	4.3223
P_{G54}	48	V_{G27}	1.0074	Q_{C37}	− 10.9761
P_{G55}	0	V_{G31}	1.003	Q_{C44}	9.1897
P_{G56}	0	V_{G32}	1.003	Q_{C45}	2.2389
P_{G59}	155	V_{G34}	1.0111	Q_{C46}	1.3214
P_{G61}	160	V_{G36}	0.9988	Q_{C48}	1.1228
P_{G62}	0	V_{G40}	1.0034	Q_{C74}	3.1048
P_{G65}	391	V_{G42}	1.0163	Q_{C79}	5.827
P_{G66}	392	V_{G46}	1.0572	Q_{C82}	19.9315
P_{G69}	546.0628	V_{G49}	0.9926	Q_{C83}	3.117
P_{G70}	0	V_{G54}	1.0247	Q_{C105}	8.2772
P_{G72}	0	V_{G55}	1.0132	Q_{C107}	1.6479
P_{G73}	0	V_{G56}	1.0195	Q_{C110}	2.1606
P_{G74}	0	V_{G59}	1.0431	T_8 (pu)	1.028
P_{G76}	0	V_{G61}	0.9984	T_{32}	1.0093

Table 16 (continued)

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G77}	0	V_{G62}	0.9993	T_{36}	0.9691
P_{G80}	477	V_{G65}	1.009	T_{51}	0.9762
P_{G85}	0	V_{G66}	1.0128	T_{93}	0.9628
P_{G87}	4	V_{G69}	0.9945	T_{95}	0.9891
P_{G89}	607	V_{G70}	1.015	T_{102}	1.033
P_{G90}	0	V_{G72}	1	T_{107}	0.9326
P_{G91}	0	V_{G73}	0.9796	T_{127}	0.9701
P_{G92}	0	V_{G74}	1.0069	VD	**0.1622**
P_{G99}	0	V_{G76}	1.0132		

Table 17 Optimal solution obtained by ISSO for the IEEE 118-bus power system with minimization of L index

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G1} (MW)	0	P_{G100}	252	V_{G77}	1.0385
P_{G4}	0	P_{G103}	40	V_{G80}	1.0622
P_{G6}	0	P_{G104}	0	V_{G85}	0.9894
P_{G8}	0	P_{G105}	0	V_{G87}	1.0502
P_{G10}	450	P_{G107}	0	V_{G89}	1.0066
P_{G12}	85	P_{G110}	0	V_{G90}	1.0034
P_{G15}	0	P_{G111}	36	V_{G91}	1.0187
P_{G18}	0	P_{G113}	0	V_{G92}	1.0198
P_{G19}	0	P_{G116}	0	V_{G99}	1.0832
P_{G24}	0	V_{G1} (pu)	1.0097	V_{G100}	1.0253
P_{G25}	220	V_{G4}	1.0351	V_{G103}	1.033
P_{G26}	314	V_{G6}	1.0059	V_{G104}	1.0227
P_{G27}	0	V_{G8}	0.9775	V_{G105}	0.9888
P_{G31}	7	V_{G10}	1.0284	V_{G107}	1.0002
P_{G32}	0	V_{G12}	0.9938	V_{G110}	1.0185
P_{G34}	0	V_{G15}	1.0272	V_{G111}	1.0843
P_{G36}	0	V_{G18}	1.0099	V_{G112}	1.021
P_{G40}	0	V_{G19}	1.0233	V_{G113}	1.0501
P_{G42}	0	V_{G24}	1.0582	V_{G116}	0.9964
P_{G46}	19	V_{G25}	1.0106	Q_{C5} (MVAR)	− 27.448
P_{G49}	204	V_{G26}	1.0641	Q_{C34}	9.1127
P_{G54}	48	V_{G27}	1.0324	Q_{C37}	− 21.1741
P_{G55}	0	V_{G31}	1.0325	Q_{C44}	5.7943
P_{G56}	0	V_{G32}	1.031	Q_{C45}	6.7776
P_{G59}	155	V_{G34}	1.0604	Q_{C46}	0.9106
P_{G61}	160	V_{G36}	1.0226	Q_{C48}	7.5556
P_{G62}	0	V_{G40}	0.9722	Q_{C74}	3.3538
P_{G65}	391	V_{G42}	1.0993	Q_{C79}	8.9954
P_{G66}	392	V_{G46}	1.1	Q_{C82}	3.4797
P_{G69}	595.7806	V_{G49}	1.0405	Q_{C83}	3.7914
P_{G70}	0	V_{G54}	0.9552	Q_{C105}	8.3628
P_{G72}	0	V_{G55}	1.0179	Q_{C107}	3.7167
P_{G73}	0	V_{G56}	0.9944	Q_{C110}	2.3961

Table 17 (continued)

Input/control variables	Value	Input/control variables	Value	Input/control variables	Value
P_{G74}	0	V_{G59}	0.9568	T_8 (pu)	0.9057
P_{G76}	0	V_{G61}	0.9962	T_{32}	1.0271
P_{G77}	0	V_{G62}	0.9949	T_{36}	1.0148
P_{G80}	477	V_{G65}	1.0454	T_{51}	1
P_{G85}	0	V_{G66}	0.952	T_{93}	1.021
P_{G87}	4	V_{G69}	0.9502	T_{95}	0.9688
P_{G89}	607	V_{G70}	0.9753	T_{102}	1.0633
P_{G90}	0	V_{G72}	1.0486	T_{107}	1.0026
P_{G91}	0	V_{G73}	1.015	T_{127}	0.9681
P_{G92}	0	V_{G74}	1.0106	L_{max}	**0.0607**
P_{G99}	0	V_{G76}	0.9987		

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