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Swarm robotics search & rescue: A novel artificial intelligence-inspired optimization approach

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ABSTRACT

In this paper, a novel heuristic algorithm is proposed to solve continuous non-linear optimization problems. The presented algorithm is a collective global search inspired by the swarm artificial intelligent of coordinated robots. Cooperative recognition and sensing by a swarm of mobile robots have been fundamental inspirations for development of Swarm Robotics Search & Rescue (SRSR). Swarm robotics is an approach with the aim of coordinating multi-robot systems which consist of numbers of mostly uniform simple physical robots. The ultimate aim is to emerge an eligible cooperative behavior either from interactions of autonomous robots with the environment or their mutual interactions between each other. In this algorithm, robots which represent initial solutions in SRSR terminology have a sense of environment to detect victim in a search & rescue mission at a disaster site. In fact, victim's location refers to global best solution in SRSR algorithm. The individual with the highest rank in the swarm is called *master* and remaining robots will play role of *slaves*. However, this leadership and master position can be transitioned from one robot to another one during mission. Having the supervision of master robot accompanied with abilities of slave robots for sensing the environment, this collaborative search assists the swarm to rapidly find the location of victim and subsequently a successful mission. In order to validate effectiveness and optimality of proposed algorithm, it has been applied on several standard benchmark functions and a practical electric power system problem in several real size cases. Finally, simulation results have been compared with those of some well-known algorithms. Comparison of results demonstrates superiority of presented algorithm in terms of quality solutions and convergence speed.

1. Introduction

With the advent of technological advances in field of computer science during recent years, researches in case of computational intelligence have attained significant attentions of scholars. In this regard, a number of optimization algorithms have been introduced based on swarm intelligence (SI). In fact, nature has been the ultimate source of inspiration for engineers in this field of science. Due to incapability of analytical-based methods such as linear programming, dynamic programming, or Lagrangian approaches for finding exact solution of large-scale or non-differentiable engineering and science problems, these heuristic based approaches which are puissant to search solution space for an approximate or a near-optimum solution in a reasonable time frame have attracted considerable attentions. They mostly have inspirations from evolution or swarm intelligence of creatures on planet earth [1].

Recently, numerous researches have been conducted in case of nature-inspired meta-heuristic optimization algorithms with the aim of reaching a methodology that has superiority over previous algorithms in terms of optimality and convergence speed by proposing a novel algorithm or by metamorphosing/hybridization of existing optimization algorithms. The common principal of all heuristic optimization algorithms is that they begin with a number of initial solutions, iteratively produce new solutions by some generation rules and then to evaluate these new solutions, and eventually report the best solution found during the search process. Some of them are summarized in Table 1.

In this paper, a new meta-heuristic optimization algorithm called Swarm Robotics Search & Rescue (SRSR) inspired by artificial intelligence of robots in the swarm robotics is proposed. In addition to several standard test functions, proposed algorithm is applied on unit commitment problem (UC) in electric power sys-

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Table 1
A literature overview of heuristic algorithms.

	Algorithm	Abbr.	Year	Inspiration
1	Ant colony optimization	ACO [2]	1992	Pheromone trail laying behavior of real ant colonies
2	Artificial Bee Colony	ABC [3]	2005	Natural foraging behavior of honey-bees
3	Artificial immune system algorithm	AIS [4]	1986	Principles and processes of the vertebrate immune system
4	Bacterial foraging optimization	BFA [5]	2002	Behaviors of E. coli bacteria during their whole lifecycle, including chemo-taxis, communication, elimination, reproduction, and migration
5	Bat Algorithm	BA [6]	2010	Echolocation characteristics of micro-bats
6	Big Bang–Big Crunch	BB–BC [7]	2006	Evolutionary theory of the universe based on the big bang and big crunch
7	Biogeography-Based Optimization	BBO [8]	2008	Geographical distribution of biological organisms (the migration behavior of island species)
8	Charged system search	CSS [9]	2010	Coulomb's law and laws of motion
9	Chemical Reaction Optimization	CRO [10]	2010	Nature of chemical reactions process
10	Cuckoo search	CS [11]	2009	Obligate brood parasitic behavior of some cuckoo species in combination with the Levy flight behavior of some birds and fruit flies
11	Cuckoo Optimization Algorithm	COA [12]	2011	Special lifestyle of Cuckoo birds and their characteristics in egg laying and breeding
12	Differential evolution	DE [13]	1997	It uses multi agents or search vectors to carry out search
13	Firefly Algorithm	FA [14]	2008	Flashing behavior of fireflies.
14	Flower Pollination Algorithm	FPA [15]	2012	Pollination process of flowers
15	Genetic Algorithm	GA [16]	1975	Natural evolution, such as inheritance, mutation, selection, and crossover
16	Gravitational Search Algorithm	GSA [17]	2009	Newton's law of universal gravitation and mass interactions
17	Grey wolf optimizer	GWO [18]	2014	Leadership hierarchy and hunting mechanism of grey wolves in nature
18	Group search optimizer	GSO [19]	2009	animal searching behavior and group living theory
19	Harmony Search Algorithm	HSA [20]	2001	Musical process of searching for a perfect state of harmony (improvisation of music players)
20	Intelligent Water Drops	IWD [21]	2009	Actions and reactions that occur between river's bed and the water drops that flow within
21	Imperialist Competitive Algorithm	ICA [22]	2007	Imperialistic competition among empires
22	League Championship Algorithm	LCA [23]	2014	Competition of sport teams in a sport league
33	Particle Swarm Optimization	PSO [24]	1995	Animal collective behavior, the movement of the swarm and the intelligence of the swarm
24	Simulated Annealing	SA [25]	1983	Metallurgic process of heating and controlled cooling of a material
25	Swine Influenza Model based Optimization	SIMBO [26]	2013	Susceptible–Infectious–Recovered (SIR) models of swine flu
26	Teaching–learning-based optimization	TLBO [27]	2012	Philosophy of teaching and learning process in a classroom
27	Variable Neighborhood Search	VNS [28]	2012	Perturbing the incumbent solution by adding some Gaussian distribution generated noise
28	Wind Driven Optimization	WDO [29]	2010	Wind flow from high pressure points to low pressure points (Newton's second law of motion)

tems. UC is an non-convex optimization problem to determine the operation schedule of the electrical generating units at every hour interval with varying loads under different operational constraints.

The main contributions of this paper compared to the previous studies can be detailed as follows:

- Proposing an artificial intelligence inspired optimization algorithm: As opposed to previous heuristic algorithms that were inspired by evolutionary or natural phenomena, presented algorithm is based on an artificial intelligence concept. Considering the fact that personal movements of robots and their internal interactions are programed by human brain, a wide range of movements and characteristics can be obtained which are mostly rare or impossible to observe simultaneously in a specific creature or phenomenon in the nature. Therefore, high flexibility of implementation and programing is achievable.
- Proposing new operators: Three new operators have been presented in proposed optimization algorithm, which are different than those of presented by previous algorithms. a) Accumulation: the first operator moves solutions to their new positions by utilizing normal distribution function. To this end, a new method for calculating mean and variance factors for each of solutions are presented. b) Exploration: the second operator may displace solutions toward/backward the best solution by a twofold master-slave concept. None of previous algorithms can lead some of solutions on counter direction of best solution during a controlled procedure to explore the entire of search space better. Besides, as opposed to previous algorithms like PSO, GA and etc. in which positions of low quality solutions were basis of their new respective positions, some positions around these solutions are basis of movement for low quality solutions in proposed operator. c) Local search: well-known operators of exponent and round

effecting on float part of variables are employed for the first time in this paper as the third operator. However, local search policy effects on limited number of solutions during each of iterations, these operators considerably accelerate convergence of algorithm when solutions are gathered near the most optimal position.

- Enjoying high robustness: Contrary to previous algorithms that their overall convergence qualities were highly dependent to several controlling parameters, SRSR has only one controlling parameter limited within a short interval that subsequently minimizes familiar challenges related to setting of controlling parameters.
- During section "progress assessment" of proposed method, position of solutions are compared with that of elite solutions using a modified approach which helps to maintain diversity of solutions; While, some optimization algorithms omitted this methodology, or this the problem about other remaining algorithms like PSO and GA results in a pre-mature convergence of algorithm and plighting in local optima.
- Enjoying high convergence in term of solution quality: In case of number of cost function evaluation in each of iterations of algorithm, this value is about 2 for proposed algorithm. However, this value for some algorithms like PSO, GA and etc. are less than SRSR, as results will confirm, quality of proposed operators suitably compensate this deficiency.

Structure of the paper is as follows: After presenting a brief review about the emergence of robotics in Section 2, Section 3 provides some explanations for swarm robotics and its practical applications in real world. Details of the proposed optimization algorithm inspired by swarm robotics based algorithm of search & rescue are described in Section 4. The performance of the proposed algorithm is illustrated in Section 5 using case studies. Concluding remarks are presented in Section 6.

2. Emergence of robotics

The development and progress of robotics in human life can be categorized into two main phases. During the first phase, electric machines that could be programmed to carry out some specific tasks have been emerged [30]. They didn't really have any obvious interactions with the real world, such as the highlighted reciprocal performance can be seen in automotive manufacturing in high-tech companies over the last century. Japanese companies were pioneer in case of employing industrial robots to different markets including pharmaceutical packaging, auto manufacturing, foundries, distribution centers and many others. As opposed to the first stage of robotics industry, novel robots are programmed not only to basically perform repetitive tasks, but also to recognize objects based on information absorbed and correspondingly respond to objects in their environment utilizing gathered information with higher accuracy. In recent years, a large number of different models have been proposed to constitute multi-robots system or swarm robotics form of collections of robots which are principle inspiration for proposed algorithm.

3. Swarm robotics, definition and application

3.1. Definition of swarm robotics

Swarm robotics is a newfangled algorithm to coordinate a large number of robots in form of multi-robot or swarm systems [31]. It is supposed that interactions of robots either with the environment or between each other result in a desired collective behavior [32]. Swarm robotics was an anonymous field of research until the model was proposed by Reynolds in 1986 [30]; A flock of birds in flight has been simulated based on local interactions and only few simple rules [30]. Independence of swarm robotics to a central wireless system and their abilities to utilize own wireless communications assist a swarm of robots to be efficient in industrial environments where the quality of receiving wireless signals is highly variable and communication failures are to be expected. Some of the highlighted characteristics of members in these swarms can be summarized as follows [33]:

i They should be completely autonomous mobile robots with ability to analyze data perceived by sensation of the real environment.
ii Based on complexities of manufacturing and control systems, number of robots in a swarm can vary from several to thousands.
iii Although, homogeneity of robots is another key feature of individuals existing in a swarm, it is seen there are a limited number of robots with specific superiorities in order to accomplish particular obligations in a mission.
iv Inability of sole individuals of swarm to reach ultimate goal desired for the entire system.
v Due to local and limited sensing and communication capabilities of robots in a swarm, coordination of individuals will be distributed and therefore, scalability becomes a property of the system.

As opposed to robots can be witnessed during routine days which mostly enjoy significant computer processing power with complex components, robots utilized in a swarm are often relatively inexpensive and simple [33]. Cooperative operation of these simple machines eliminates the necessity to more powerful and expensive robot. In order to satisfy such the necessity, oblivion should be an inseparable feature of robots in such the style which means they cannot remember observations or computations performed. In the best state of construction, they can remember only a limited number of previous steps. Based on the environment in which the swarm will be utilized, different communication systems like radio frequency, infrared or any other types of wireless transmission systems are employed. With respect to the fact, the sensing range of robots may vary from zero to visibility domain. Unlike the distributed computing in which many computers work on a single large task, each individual in the swarm-style robotics deals with unique stimuli. For instance, each robot might be in a different area at a given time.

3.2. Search & rescue application of swarm robotics

Research for applications of swarm robotics in the field of target search has grown significantly during recent years [32]. Problems related to applications of swarm robotics can be categorized into two classes. First class includes pattern based problems (*e.g.* self-organizing grids, migration, cartography, aggregation and area coverage) while destination in the second class is object existence (*e.g.* searching for ore veins in wild region, locating targets in an unknown environment, foraging, detecting the odor sources and search & rescue (S&R) mission accomplishment for a victim in a post-disaster area) [34].

In this regard, the focus of majority of contributions has been on groups of machines which have relatively small number of members. However, a swarm having 1024 single robots was demonstrated by Harvard in 2014 and that has been the largest so far [35]. Swarm robotics system is mostly common for the tasks requiring a large area of space (*e.g.* the tasks that cover large areas) [40–43]. A simple example is searching and collecting multiple targets in an open area [42]. The area might be very large and the

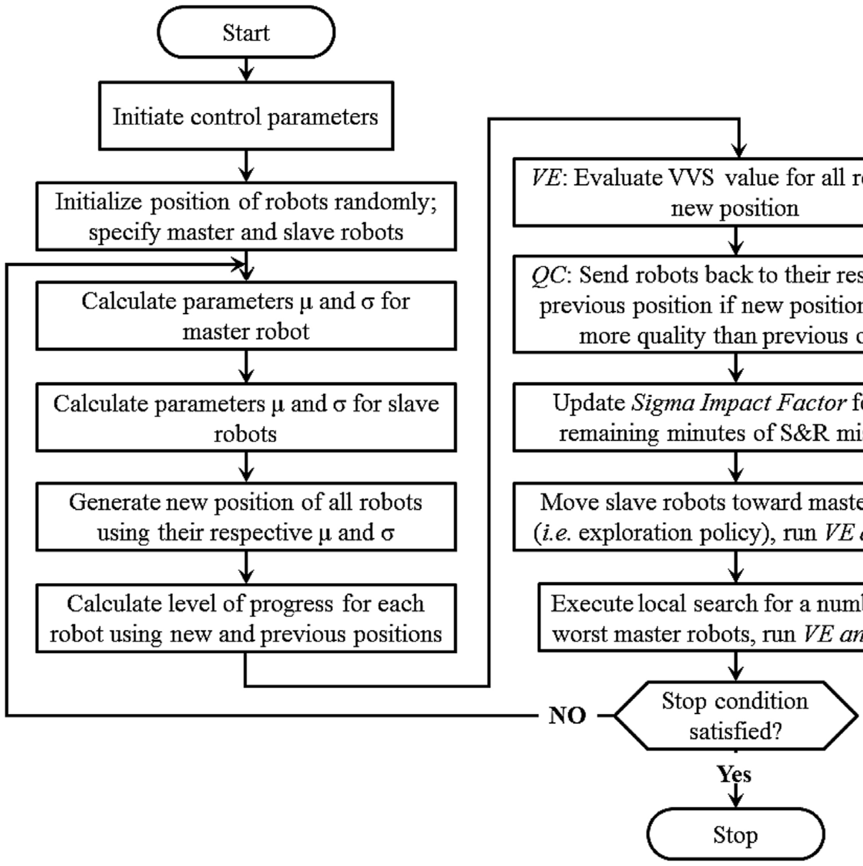

Start
Initiate control parameters
Initialize position of robots randomly; specify master and slave robots
Calculate parameters μ and σ for master robot
Calculate parameters μ and σ for slave robots
Generate new position of all robots using their respective μ and σ
Calculate level of progress for each robot using new and previous positions
VE: Evaluate VVS value for all robots in new position
QC: Send robots back to their respective previous position if new position is not more quality than previous one
Update Sigma Impact Factor for the remaining minutes of S&R mission
Move slave robots toward master robot (i.e. exploration policy), run VE and QC
Execute local search for a number of worst master robots, run VE and QC
Stop condition satisfied?
NO
Yes
Stop

Fig. 1. Flow chart of the proposed SRSR algorithm.

swarm can take advantage of the parallel searching with several small groups within the sensing ranges of the robots.

Besides, research for applications of swarm robotics in the field of target search has grown significantly during recent years for situations in which search mission is associated with high level of danger or in inaccessible working places. To this end, applications of swarm robotics in forms of autonomous armies in military and S&R task accomplishment in endangered semi-ruined environments are two most highlighted. In fact, one of the most promising applications of multi-robots and swarm robotics concerns about S&R process; in which an unsafe semi-destroyed structure after a disaster should be explored to rescue a victim [34,35]. This procedure was the inspiration of proposed optimization algorithm. In case of places that are not reachable for rescue workers to safely detect the presence of life using passive infrared sensor (PIR sensor), a swarm of robots with pre-specified sizes can be highly effective.

It is notable that there are mainly two types for interactions among individuals in a swarm of robots. In first and most common type, no individual has superiority over others; while in second type which is known as master-slave swarm robotics [36,37], however all individuals have same characteristics, each member of swarm has ability to play role of leader (master robot) in some periods of mission accomplishment. This type of swarm robotics as basis of proposed algorithm has been detailed in Section 3.3.

3.3. Master-slave swarm robotics

The communication system among robots is one of primary issues in design of a swarm. However, several communication systems like Bluetooth, IR and ZigBee have been proposed and currently employed for communication among individuals of swarms, no strong evidence of superiority can be found in case of one of these systems. In this research, master/slave technique as the communication system is used [36,37]. In this type of communication system, the swarm consists of a single master robot and slave robots. The master robot sends its current position to slave robots to track its position in addition to their local searches during each interval of S&R mission. Therefore, only the communication between the each slave robot and present master robot is necessary. The master robot controls the entire swarm. In fact, the master robot should communicate with the other robots to help them identify their relative location to the master robot.

In this system, all robots should be programmed to act both the roles of master and slave; and the role of master robot can be change among all the robots existing in a swarm iteratively based on quality robots position in search space. The slave robots will depend on master robot to avoid getting stuck at local optima. Low cost of the final system compared to the other options such as Bluetooth, simple structure of the antenna and possibility to have flexible antenna, short range of communication which brings security and no interfering signals and possibility to setup a leader-less swarm structure with satisfactory efficiency are main advantages of slave-master based communication system. Detailed procedure and interactions between members of a slave-master based swarm of robots based S&R mission is provided in Section 4.

4. Swarm Robotics Search & Rescue (SRSR) algorithm

In this section, the structure of proposed algorithm is described based on cooperative behavior of a swarm of robots to search a victim in a post-disaster location. Flowchart depicted in Fig. 1 shows the procedure of algorithm implementation. As like as other evolutionary optimization algorithms, it starts with creation of a

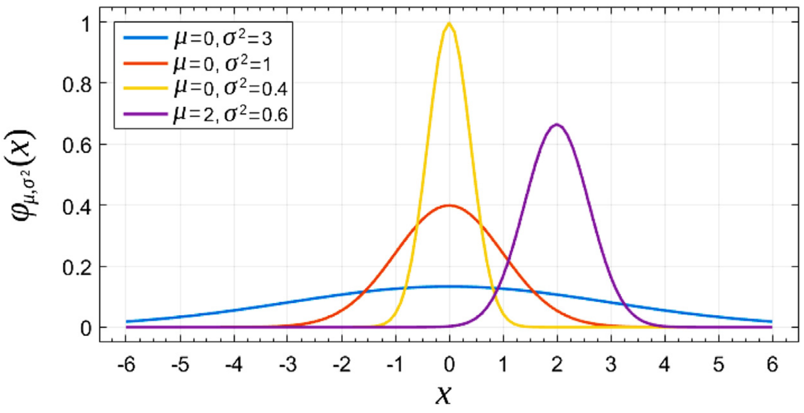


Fig. 2. Normal distribution probability density function.

population of robots. In next step, robots should be distributed in catastrophe areas. Then, they start to search and appraise area near their position and by utilization of high-tech sensors mounted on robots for attaining specified vital signs of the victim, mostly human. Based on data gathered by robots, the superior individual among the swarm plays role of the *master* robot and should conduct group to promoted situations; while it is mandatory for other robots to perform as the *slaves*. In such the condition, quality of a robot position is completely related to its sense of environment and, subsequently its ability to track vital signs of victim. It is noteworthy that all robots in a swarm have similar construction specifications, and therefore their abilities to response to environmental signals and to analyze the received information are identical as well. During the search and rescue (S&R) mission, with leadership of the robot named master due to highest peripheral perception from victim, three policies including 1) Accumulation: gathering of slave robots in a position near the position of master robot, 2) Exploration: search of distance between slave and master robots by slave robots and, 3) Local search: search of specified number of robots surrounding the position of master robot should be accomplished.

As opposed to individuals in natural swarms, semi-advanced robots in a homogeneous group have a limited ability to record previous steps. This characteristic assists members to return to previous positions if they don't reach a favorable position during the period of mission accomplishment. However, due to the mentioned hardware limitations of robots in a swarm with large number of members which are designed for a coherent behavior in a rescue mission, the chip design of robots will not permit them to record more than one or two previous steps. Besides, the robustness of swarm robotic systems comes from the implicit redundancy in the swarm. This redundancy allows the swarm robotic system to degrade peace-fully making the system less prone to catastrophic failures. For instance, swarm robotic systems can create dynamic communication networks in the battlefield. The first hypothesis for these swarms assumes that each individual owns a unique ID for communication and cooperation. Such networks can enjoy the robustness achieved through re-configuration of the communication nodes when some of the nodes are hit by enemy fire. However, there are some limitations for swarm like central automatic control by which slave robots are restricted to communicate solely with master robot. While a slave robot reaches a position better than that of master robot, it should guide swarm for rest of mission as the master robot; while prior master will play role of a slave robot. In fact, they should exchange their duties and responsibilities of S&R mission for remaining minutes ahead. The rest of paper illustrates how S&R mission is modeled based on swarm robotics for optimization task.

4.1. Generating initial swarm of robots

In order to obtain a global solution of an optimization problem, the first step is to form decision variables of problem as an array. In different codifications of optimization algorithms, this array has been called with different names. For instance, it is named as chromosome, social-political position of a country and habitat in GA, ICA and COA, respectively. In the proposed algorithm, vector of decision variables is called *robot position*. In an optimization problem with N_{var} decision variables, each initial solution is composed of an array with dimension $1 \times N_{\text{var}}$ shows the position of a robot in search area. This position is defined by Eq. (1):

$$Position^{i}_{robot} = [x_1, x_2, \ldots., x_{N_{var}}], i = 1, 2, , \ldots., N_{robots} \tag{1}$$

Variables $x_1, x_2, \ldots., x_{N_{var}}$ can be floating point numbers. Value of victim's vital signs (VVS) monitored by each robot is defined by Eq. (2):

$$VVS = f\left(Position^{i}_{robot}\right) = f([x_1, x_2, \ldots., x_{N_{var}}]), i = 1, 2, , \ldots., N_{robots} \tag{2}$$

Where f is referred to optimization function. Considering N_{robots} as number of robots in initial swarm, a matrix with dimension of $N_{\text{robots}} \times N_{\text{var}}$ is generated as initial population of robots. In a solution search space with maximum and minimum limits of $Var_{\max}$ and $Var_{\min}$, respectively; initial position of a robot can be obtained by Eq. (3):

$$Position_{robot} = Urnd\left(Var_{\min}, Var_{\max}, Var_{size}\right) \tag{3}$$

Function *Urnd* generates an array of random floating-point numbers from continuous uniform distribution with lower and upper endpoints specified by $Var_{\min}$ and $Var_{\max}$, respectively; and $Var_{\text{size}} = 1 \times N_{\text{var}}$.

As mentioned, after generating initial solutions and evaluating of initial population, master and slave robots are determined based on fitness of *VVS*s. Then, three main policies of algorithm including accumulation, exploration, and local search are implemented as follows:

4.2. Accumulation

During the first policy of algorithm, all slave robots should move to a position near the position of the master robot aiming at ameliorating its current sense of *VVS*. This accumulation nearby the position of best robot is implemented with random movements and by utilizing normal probability distribution function (PDF). The probability density of normal distribution is given by Eq. (4):

$$y = f[x|\mu, \sigma] = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{4}$$

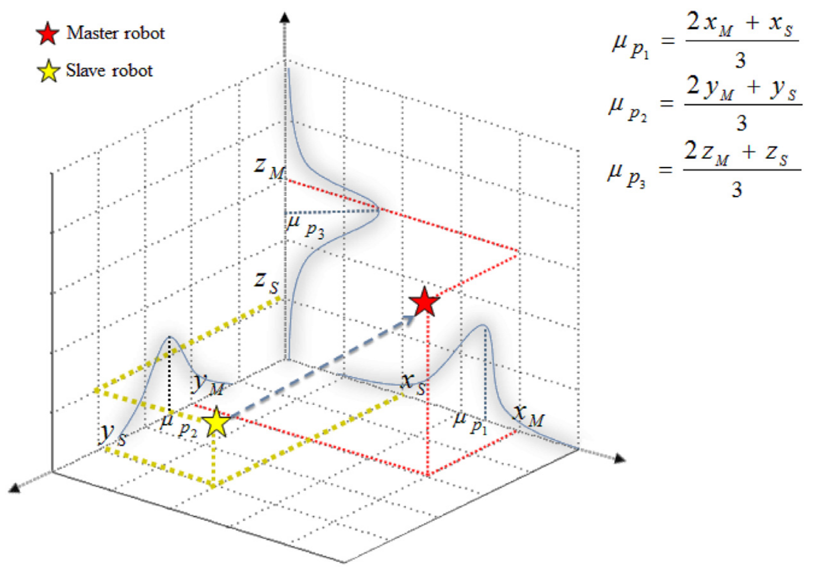

Master robot
Slave robot
$\mu_{p_1} = \frac{2x_M + x_S}{3}$
$\mu_{p_2} = \frac{2y_M + y_S}{3}$
$\mu_{p_3} = \frac{2z_M + z_S}{3}$
z_M
μ_{p_3}
z_S
y_M
x_S
x_M
y_S
μ_{p_2}
μ_{p_1}

Fig. 3. Movement of slave robot toward master robot by the accomplishment of accumulation policy.

Here parameter μ is mean or expectation of distribution and parameter σ is its standard deviation with its variance then σ^2. A random variable with a Gaussian distribution is said to be normally distributed and is called a normal deviate. If $\mu = 0$ and $\sigma = 1$, the distribution is called the standard normal distribution denoted by$N(0, 1)$. As it can be seen in Fig. 2, with variations of two parameters μ and σ, different ranges of PDF based random floating numbers can be obtained.

The master robot transmits its current position to slave robots employing predesigned communication systems like Bluetooth technology, global positioning system (GPS) and *etc.* as an accumulation command. Subsequently, slave robots start to change their position toward the position of the master robot.

Comparing normal PDF to some other well-known PDFs like Weibull, Gamma or Pareto, it should be mentioned that the most important aspect about these functions is that these are skewed and asymmetric. These distribution functions are mostly used to model phenomena in which generated points should be distributed with high probabilities at first/ending stages of phenomenon. On the contrary, the great power of the normal distribution is that the concept of Master-Slave in a swarm of robots can be transformed into a normal distribution *via* Central Limit Theorem [38]. Moreover, it also serves a physical manifestation. Due to fact that there is no certain justification about superiority of movement direction for an individual in a swarm of robots with limited level of intelligence, especially during first iterations, robots should explore both directions with same probability to maintain diversity and also to prevent plighting in local minimums. Using Weibull, Gamma or Pareto distributions, probability to search on one direction toward the master robot will be dominant and logically, because of high convergence toward local minimums during first iterations of algorithm execution, an extensive exploration of search space for global optimum cannot be achieved.

Values μ and σ for master and slave robots can be obtained as follows:

4.2.1. *Calculation of parameters μ and σ for master robot*

As aforementioned, master robot calls slave robots up to its current position with aim of directing population to location with the maximum likelihood of victim presence. As long as slave robots are accumulating in position of master robot, it starts a local search nearby the stated position. In fact, by execution of such the search, master robot tries to improve its situation during period other robots are moving toward position in which maximum *VVS* has been found. Considering C_1 as first control parameter, values μ and σ for master robot are defined by Eqs. (5) and (6), respectively:

$$\sigma_{robot[M]} = r \tag{5}$$

$$\mu_{robot[M]} = \left(1 + (-1)^{Eit+1} \times \sigma_{robot[M]}\right. \\ \left. / \left(\max\left(0, (-1)^{Eit+1}\right) \times (1 - C_1) + 1\right)\right) \times Position_{robot[M]} \tag{6}$$

r is a random number within [0,1], *Eit* denotes elapsed time of S&R mission in SRSR terminology, refers to number of iterations in algorithm codification and $Position_{robot[M]}$ is position of master robot.

4.2.2. *Calculation of parameters μ and σ for slave robots*

During implementation procedure of accumulation policy, all slave robots should be relocated by their own parameters μ and σ. Parameters for slave robots are defined by Eqs. (7) and (8):

$$\sigma^i_{robot[S]} = SCF^i \times \left(Position_{robot[M]} - Position^i_{robot[S]}\right) \\ + r^2 \times Position^i_{robot[S]}(j)\,|_{\left(Position_{robot[M]}(j) - Position^i_{robot[S]}(j)\right) < 0.05},\ i = 1, \ldots., N_{slaves}; j = 1, \ldots., N_{var} \tag{7}$$

$$\mu^i_{robot[S]} = C_1 \times Position_{robot[M]} + (1 - C_1) \times Position^i_{robot[S]},\ i = 1, \ldots., N_{slaves} \tag{8}$$

SCF^i is a correction factor for parameter σ corresponding to slave robot *i*. Calculation method of *SCF* value has been detailed in Section 4.2.5. The schematic representation for calculation procedure of new position of a slave robot by executing accumulation policy in relation to master robot is shown in Fig. 3. It should be mentioned that the location $(\mu_{p_1}, \mu_{p2}, \mu_{p3})$ enjoys maximum likelihood to be chosen as the next position of slave robot. However, based on the variance obtained for each of the axes which refer to decision variables, the locations near the location of master robot might be proportionally chosen with lower probabilities.

4.2.3. Generating new positions

In this section, new position of master and slave robots by utilizing parameters μ and σ corresponding to each robot should be determined.

$$New\ Position_{robot[i]} = Nrnd\left(\mu_{robot[i]}, \sigma_{robot[i]}\right),\ i = Master, Slaves \quad (9)$$

Function *Nrnd* generates an array of random floating point number from normal PDF with mean parameter μ and standard deviation parameter σ obtained from two previous sections. It is noteworthy; this equation is valid to determine new position for both master and slave robots. In order to bound new obtained positions in range of search space, following equations are utilized:

$$New\ Position_{robot[i]}(j) = \max\left(Var_{min}(j), New\ Position_{robot[i]}(j)\right),$$
$$i = Master, Slaves;\ j = 1, \ldots, N_{var} \quad (10)$$

$$New\ Position_{robot[i]}(j) = \min\left(Var_{max}(j), New\ Position_{robot[i]}(j)\right),$$
$$i = Master, Slaves;\ j = 1, \ldots, N_{var} \quad (11)$$

$$New\ VVS_{robot[i]} = f\left(New\ Position_{robot[i]}\right),\ i = Master, Slaves \quad (12)$$

4.2.4. Progress assessment

In nature, there are a large number of creatures with some elements of cooperative behaviors. In animal communities, many empirical evidences suggest that performance of a cooperative behavior may not be desirable in a period of time and it was impossible to return to previous situation. Lack of a temporary memory to record accurate previous situation and time variant features of environmental elements are two key factors for occurrence of these types of events. However, such the happenings are not mostly probable in artificial intelligence territory. As an illustration, a simple robot in a S&R swarm with moderate functionality which has ability to record one previous step can change its current position to previous one if desired improvements are not achieved in new position. This capability has been considered for rescuer robots in swarm robotics. Mathematic formulation of this characteristic is defined by Eq. (13):

$$\begin{aligned}&if\ \ NewVVS^{j}_{robot[i]} < VVS^{j}_{robot[i]},\ i = Master, Slaves;\ j = 1, \ldots, N_{var}\\ &VVS^{j}_{robot[i]} = NewVVS^{j}_{robot[i]}\\ &Position_{robot[i]} = NewPosition_{robot[i]}\\ &end\end{aligned} \quad (13)$$

However, it should be mentioned that by implementation of this policy during every minute of the S&R mission for all robots, they rapidly gather at a local optimum location and algorithm will lose its diversity factor gradually in search process. Therefore, after relocation of robots to their new position and sorting them based on their new *VVS* quality, one of values 50% or 100% of population should be selected randomly by algorithm. If 50% is selected, robot population should be divided to two groups. Then, robots in the first group which enjoy higher *VVS* values are permitted to reside in new positions, if $NewVVS_{robot} < VVS_{robot}$; otherwise, they are subject to return to previous positions. Whereas, members of the second group should reside in new positions without any consideration of improvement in *NewVVS* to maintain diversity of whole the population. If value 100% is selected, method employed for the first group should be utilized for all members of population.

4.2.5. Calculation of SCF

After settling of robots at their new position at the end of each time interval of S&R mission, *SCF* value should be modified for coming one minute (refers to next iteration in algorithm implementation) based on *VVS* change of robots in current iteration. That is the robot which enjoys highest *VVS* change compared to previous one minute should be considered as basis for modification of robots movement in coming one minute of S&R mission. Calculation procedure of *SCF* is detailed in the following steps:

Step 1: Let *SIF* = 6 as an initial value for the first iteration (algorithm is not sensitive to this value, because value of this temporary variable will be modified iteratively).

Step 2: Calculate $SCF_i = SIF \times r_i$, i = 1, ..., N_{robots}; r_i is random number within [0,1] corresponding to robot *i*.

Step 3: Calculate $VVS^{i}_{Movement} = VVS^{i}_{robot} - NewVVS^{i}_{robot}$, $i = 1, \ldots, N_{robots}$

Step 4: Select index *i* which refers to robot enjoys maximum$VVS_{Movement}$

Step 5: Calculate $SIF = \left(1 + \left(\max\left(\overline{Var_{\max}} - \overline{Var_{\min}},\right)\right) \times r\right) \times SCF_{\max}$; $SCF_{\max}$ is value of *SCF* corresponding to robot which is selected in step 4.

Step 6: Limit *SIF* value obtained in previous step within $\left[0, \max\left(\overline{Var_{\max}}\right)\right]$, derived from six sigma theory [39].

Step 7: Go step 2 for new iteration.

It is noteworthy variable $VVS^{i}_{Movement}$ in step 3 should be determined before implementation of "Section 4.2.4 progress assessment" in which variables *Position* and *VVS* are updated based on improvements of robots; otherwise, it is probable about some of robots to return to their respective position if new positions are not more justified in term of VVS_{robot} value.

4.3. Exploration

Exploration policy is another main operator of proposed algorithm by which slave robots are allowed to search spaces around themselves in a direct path toward/backward master robot. New position of slave robots by execution of exploration policy can be obtained by Eq. (14):

$$\begin{aligned}&NewPosition^{i}_{robot[S]} = r \times Position^{i}_{robot[S]}\\ &+GB \times \left(Position_{robot[M]} - Position^{i}_{robot[S]}\right) \times MF,\ i = 1, \ldots, N_{slaves}\end{aligned} \quad (14)$$

Variable *GB* = ±1 is selected randomly and vector of *movement factor* (*MF*) is calculated by$\max\left(1, |Position_{robot[M]} - Position_{robot[WS]}|\right)$ at the end of each iteration; here index *WS* refers to slave robot with the worst *VVS*. Parameter *MF* can control convergence speed and accuracy of search at different intervals of algorithm execution. This movement is shown in Fig. 4. As it can be seen, a random percent of current position of a slave robot is added to/subtracted from a factor of direct path from position of slave robot to position of master robot. In fact, the first term of exploration equation changes distance and initial angle of position of a slave robot with respect to master robot (first step), randomly; while the second term of exploration equation moves position of slave robot toward/backward master robot (second step). After creating new position of slave robot, all steps proposed in Section "4.2.4 progress assessment" should be implemented to determine optimal position of slave robots in current one minute of S&R mission.

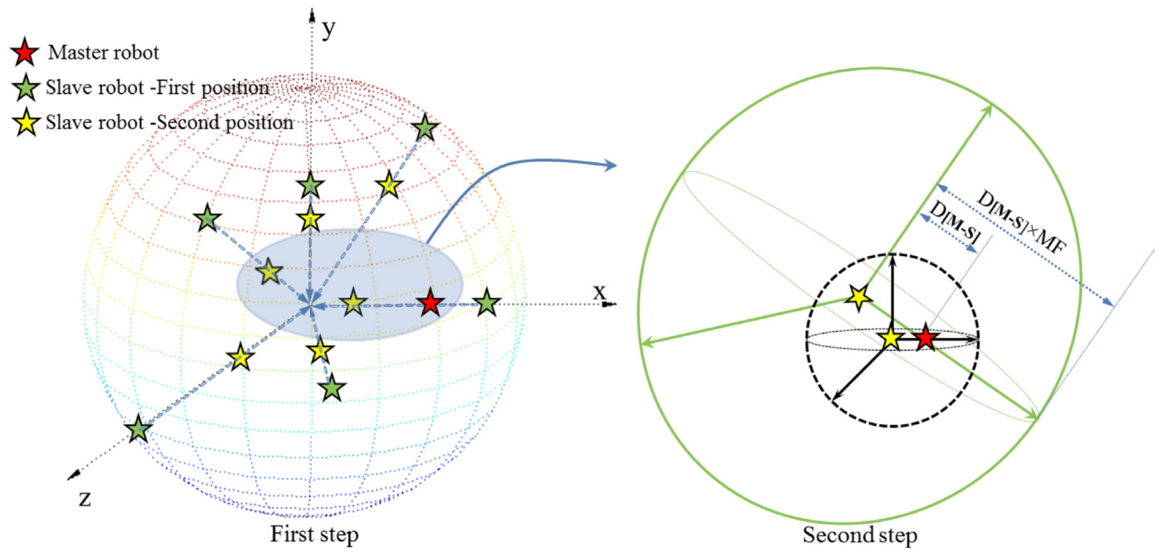


Fig. 4. Two steps of exploration procedure.

4.4. Local search

In this policy, a specified number of robots which have lowest qualities perform as worker robots. These robots are assigned to a local search around the position of master robot. In fact, this policy is an extra accurate search by which worker robots, that refer to low quality solutions in optimization algorithm, are permitted to improve their position. However, residing of worker robots at new positions is possible only when they reach a position better than position of robot enjoying second rank. Otherwise, they should return to the previous position after an unsuccessful search. In order to implement such an expression, some arithmetic operators with elementary operations have been employed to determine the new position of worker robots as follows:

4.4.1. Round operator

$$NewPosition^{1}_{robot[W]} = sign\left\{round^{+}\left(|Position_{robot[M]}|\right)\right\}_{robot[M]} \quad (15)$$

$$NewPosition^{2}_{robot[W]} = sign\left\{round^{-}\left(|Position_{robot[M]}|\right)\right\}_{robot[M]} \quad (16)$$

Operators $round^{+}(\bar{x})/round^{-}(\bar{x})$ round elements of $\bar{x}$ to nearest integers greater than/less than or equal to $\bar{x}$, respectively; and operator $sign\{\omega\}_{\psi}$ reflects signs of $\bar{\psi}$ to $\bar{\omega}$ element by element.

4.4.2. Exponential operator

$$New\ Position^{3}_{robot[W]} = sign\left\{Int\left\{Position_{robot[M]}\right\} + \left(Fra\left\{Position_{robot[M]}\right\}\right)^{\frac{1}{e_1}}\right\}_{robot[M]} (17)$$

$$New\ Position^{4}_{robot[W]} = sign\left\{Int\left\{Position_{robot[M]}\right\} + \left(Fra\left\{Position_{robot[M]}\right\}\right)^{e_2}\right\}_{robot[M]} (18)$$

Functions $Int\left\{\bar{\rho}\right\}$ and $Fra\left\{\bar{\rho}\right\}$ return integer and fractional parts of elements of $\bar{\rho}$, respectively. Parameters e_1 and e_2 are two random integers within [2,4].

4.4.3. Combined operator

This operator is retrieved from crossover policy in GA. In fact, new position of worker robot 5 is a combination of $NewPosition^{3}_{robot[W]}$ and $NewPosition^{4}_{robot[W]}$ with random shares of P_1 and P_2, respectively; while, $P_1 + P_2 = 100\%$.

$$New\ Position^{5}_{robot[W]} = \left[\left[P_1\%\left(NewPosition^{3}_{robot[W]}\right)\right]\ \left[P_2\%\left(NewPosition^{4}_{robot[W]}\right)\right]\right] (19)$$

It is noteworthy such implementation is accomplished about a certain number of decision variables, not all variables of position array to prevent sudden chaotic changes in position of obtained solutions.

4.5. Control parameters

Control parameters of algorithm are as follows:

i Mu factor [C1]: controls mean values for master and slave robots. This parameter controls dominance degree of the master robot.
ii Movement factor [C2]: determines movement pace of robots during exploration policy
iii Sigma factor [C3]: determines level of divergence of the slave robots from master robot.
iv Sigma limit [C4]: limits value of sigma factor

In this algorithm, control parameters C2, C3 and C4 are automatically tuned; while C1 should be adjusted by user within [0.5, 0.85].

5. Case study and results

In this paper, the effectiveness of the presented method has been assessed in two scenarios. For first scenario, a number of standard test functions have been employed; while, in second scenario, the proposed method has been applied to obtain optimum scheduling table for medium-scale (10 unit system) to large-scale (100 unit system) thermal electric power generating systems. The proposed heuristic algorithm has been implemented on an Intel® Core™ i5–460 M Processor (3 M Cache, 2.53 GHz).

5.1. Scenario 1: standard benchmark functions

For this scenario, the proposed method has been applied to a set of unimodal (F1–F10; for scales of small (D1), medium (D2) and

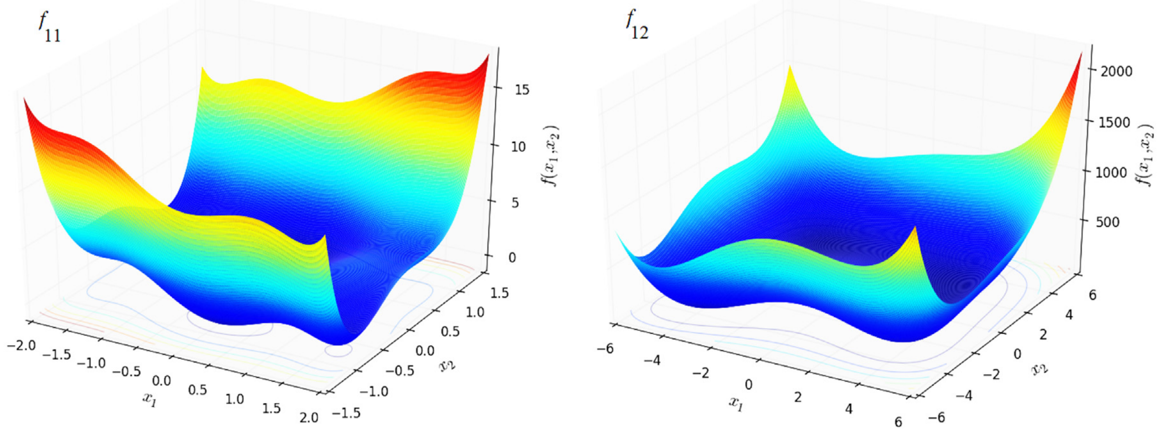


Fig. 5. Multimodal functions with a few local minima (f_{11}: Six Hump Camel Back and f_{12}: Himmelblau).

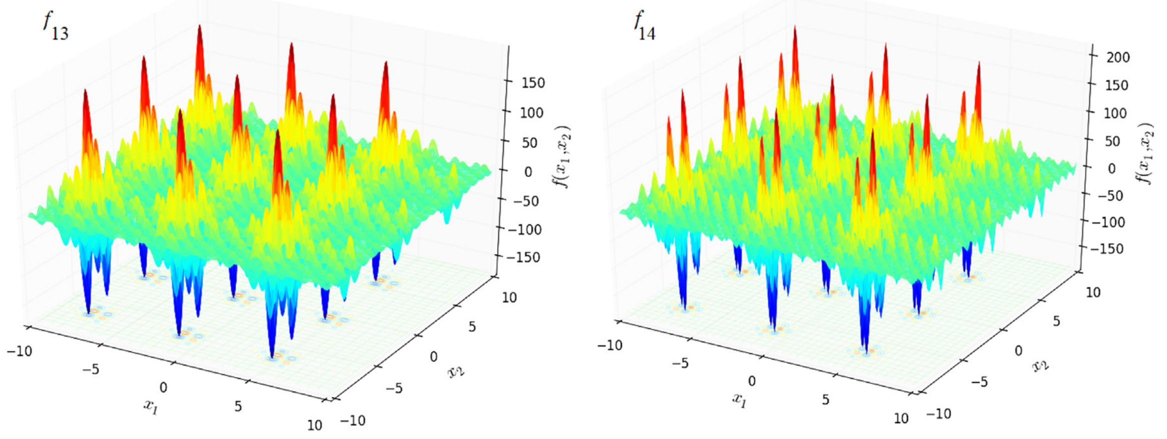


Fig. 6. Multimodal functions with many local minima (f_{13}: Hansen and f_{14}: Shubert).

large (D3)) and multimodal (F11–F14) standard benchmark functions. These functions have been detailed in Tables 2 and 3. The proposed algorithm has been run for 50 times. In order to guarantee a fair comparison among different algorithms and to avoid consideration of execution time as the comparison index (because different qualities of codification for a same problem formulation may result in different execution times), maximum number of function evaluations (NFE) is considered as stop criterion of algorithm implementation. NFE parameter has been set to 5000 in case of unimodal and 10000 in case of multimodal benchmark functions. For all other algorithms, the maximum NFE has been set to that of the proposed algorithm. Multimodal functions include two functions with a few local minima (F11 and F12 depicted by Fig. 5) and two functions with many local minima (F13 and F14 depicted by Fig. 6).

In implementation procedure of algorithm, stop criterion is defined by Eq. (20):

$$f_{end.it}(robot_{[M]}) - global\min \leq StC \tag{20}$$

$f_{end.it}(robot_{[M]})$ is cost of the best obtained solution at last iteration of algorithm and StC is stopping criterion of the algorithm, when it converges into 10^{-6} and 10^{-3} tolerance in cases of unimodal and multimodal functions, respectively. Mean and standard deviation for obtained results are calculated by Eq. (21):

$$Std.dev = \left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{1}{2}} \tag{21}$$

x_i is vector of solutions resulted by runs of program and $\bar{x}$ is mean value of solutions:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n}x_i \tag{22}$$

Obtained results including best (min), arithmetic average (mean), worst (max) and standard deviation (Std. dev.) after 50 independent executions of proposed SRSR optimization algorithm have been compared with those of TLBO, ABC, ICA, BBO, GSA, PSO and DE in Tables 4–6 for dimensions D1-D3, respectively. As it can be deduced from Table 4, proposed SRSR methodology shows the best performances among presented methods; while the worst performance is related GSA. ABC and ICA enjoy relatively equal performances and also weaker performances compared to SRSR and TLBO. Obviously, proposed algorithm demonstrates its superiority and efficiency in cases of reaching global solution and lower standard deviations. Moreover, in case of max (worst) solution, proposed algorithm has shown its excellence in comparison task for all benchmark functions. Although, BBO presents a better performance than GSA, solutions obtained by executions of these algorithms do not enjoy expected quality to be comparable with other algorithms. Moreover, considering little changes in ranking, PSO and DE provide solutions relatively as similar as TLBO in most of the cases.

Referring to Table 5 and 6, superiority of SRSR method can be highly demonstrated by comparison of obtained results with those of literature review for medium and large scale unimodal problems.

Table 2
Standard unimodal test functions.

Func	Definition	Interval	Global minimum	Dimension		
				D1	D2	D3
F1	$f(x)=\sum_{i=1}^{N} x_i^2$	[−100,100]	0	10	50	200
F2	$f=\sum_{i=1}^{D}[100(x_i{}^2-x_{i+1})^2+(1-x_i)^2]$	[−10,10]	0	2	50	200
F3	$f(x,y)=y\sin(4x)+1.1x\sin(2y)$	[−10, 10]	−19.8623	2	–	–
F4	$f=10n+\sum_{i=1}^{n}(x_i{}^2-10\cos(2\pi x_i))$	[−5.12,5.12]	0	3	50	200
F5	$f(x)=-20\exp(-0.2\sqrt{\frac{1}{30}\sum_{i=1}^{D}x_i{}^2)-\exp(\frac{1}{30}\sum_{i=1}^{D}\cos 2\pi x_i)}$	[−30,30]	8.8818e-16	10	50	200
F6	$f(x)=\sum_{i=1}^{N}(x_i^2+x_i)\cos(x_i)$	[−10,10]	−100.22375 × D	2	50	200
F7	$f(x,y)=x\sin(4x)+1.1y\sin(2y)$	[−10,10]	−18.5547	2	–	–
F8	$f(x)=\sum_{i=1}^{N}(\lvert x_i\rvert-10\cos(\sqrt{\lvert x_i\rvert})$	[−10,10]	−10 × D	10	50	200
F9	$f(x)=0.5+\frac{\sin^2(\sqrt{(x_1^2+x_2^2)})-0.5}{1+0.001(x_1^2+x_2^2)}$	[−10,10]	0	2	–	–
F10	$f(x)=1+\sum_{i=1}^{N}\frac{x_i^2}{4000}-\prod_{i=1}^{N}\cos(\frac{x_i}{\sqrt{i}})$	[−10,10]	0	10	50	200

Table 3
Standard multimodal test functions.

Func	Definition	Interval	Global minimum	Global peaks
F11	$f(x)=\left(4-2.1x_1^2+\frac{x_1^4}{3}\right)x_1^2+x_1x_2+\left(-4+4x_2^2\right)x_2^2$	$x_1\in[-1.9,1.9]\ x_2\in[-1.1,1.1]$	−1.03162	2
F12	$f(x)=\left(x_1^2+x_2-11\right)^2+\left(x_1+x_2^2-7\right)^2$	$x_1\in[-6,6]\ x_2\in[-6,6]$	0	4
F13	$f(x)=\left(\sum_{i=1}^{5}i\cos((i-1)x_1+i)\right)\times\left(\sum_{j=1}^{5}j\cos((j+1)x_2+j)\right)$	$x_1\in[-10,10]\ x_2\in[-10,10]$	−176.541	18*
F14	$f(x)=\left(\sum_{i=1}^{5}i\cos((i+1)x_1+i)\right)\times\left(\sum_{j=1}^{5}j\cos((j+1)x_2+j)\right)$	$x_1\in[-10,10]\ x_2\in[-10,10]$	−186.730	18*

* indicates minimum number of peaks for 2D function.

Convergence curves of the proposed algorithm *versus* NFE for different benchmark functions are compared with those of ABC, TLBO, ICA, BBO and GSM in Fig. 7. In the case of single objective functions, superiority of SRSR over other algorithms in term of the solution quality is evident; however such the superiority cannot be observed for all benchmark functions in term of convergence pace. It should be mentioned that convergence quality of algorithms is completely related to features of benchmark functions. Needless to say, level of adaptability of an optimization algorithm cannot be determined by applying to a limited number of problems. As an illustration, GSM algorithm does not provide quality solutions in most of cases, while its convergence speed surpasses that of other algorithms for function F1.

In case of multimodal functions (F11–F14), results of comparison of SRSR with other algorithms based on success times (number of runs in which all global peaks have been found), mean (average final value of all runs of algorithm) and average number of optima found (the average number of peaks found over 50 runs with $StC=1\times10^{-3}$) are detailed in Table 7. As it can be seen, maximum number of success times has been obtained by SRSR. Considering more challengeable feature of multimodal benchmark functions compared to unimodal functions, success rates for multimodal functions are not as high as unimodal functions. In case of multimodal functions F11–F14, TLBO and ABC have better performances than ICA in most of cases. It is noteworthy, with the increment of complexity of benchmark functions from F11 to F14, quality of solutions are reduced. As an illustration, average optima found by SRSR for the function F11 is 2 where there are two global peaks (100% success rate); However, there are 18 global peaks for function F14 and the best average optima found is 16.18 by SRSR (89.9% success rate). Such the statement is true about number of success times and mean values as well. Results obtained by BBO and GSA implementations show none of them are capable of comparing with other algorithms. However, TLBO has approximately equal performances to SRSR about functions F11 and F12, superiorities of

Table 4
Comparison of best obtained solutions from different algorithms (unimodal function); dimension: D1.

		ABC	TLBO	ICA	BBO	GSA	PSO	DE	SRSR
F1	Min (best)	0.0368	3.24×10^{-06}	51.6464	4.4543	5.8254	4.16×10^{-14}	41.82×10^{-09}	0
	Mean	0.4282	9.34×10^{-05}	196.9432	17.3496	15.2565	8.99×10^{-12}	4.57×10^{-08}	0
	Max (worst)	1.4496	0.0011	606.8374	52.3666	24.0362	1.83×10^{-10}	2.73×10^{-07}	0
	Std. dev.	0.3499	1.82×10^{-04}	117.6103	10.7962	4.0361	2.70×10^{-11}	5.95×10^{-08}	0
F2	Min (best)	5.61×10^{-07}	6.83×10^{-05}	1.06×10^{-05}	0.0306	0.0086	3.13×10^{-16}	1.82×10^{-18}	0
	Mean	0.0017	2.42×10^{-02}	0.0272	1.1487	0.349	374×10^{-09}	1.96×10^{-09}	0
	Max (worst)	0.0177	0.1654	0.5372	5.5865	1.1296	4.95×10^{-08}	7.14×10^{-08}	0
	Std. dev.	0.0035	0.0328	0.0787	1.3068	0.2913	1.03×10^{-08}	1.07×10^{-08}	0
F3	Min (best)	−19.8623	−19.8623	−19.8623	−19.7337	−19.7744	−19.8623	−19.862	−19.8623
	Mean	−19.8623	−19.8621	−19.786	−18.3463	−18.5486	−17.0653	−19.337	−19.8623
	Max (worst)	−19.8623	−19.8582	−18.5916	−16.8589	−17.4261	−11.6434	−17.494	−19.8622
	Std. dev.	4.48×10^{-10}	5.71×10^{-04}	0.3048	0.6638	0.5188	1.9560	0.96656	1.69×10^{-06}
F4	Min (best)	1.99×10^{-06}	0	2.95×10^{-05}	0.011	1.0318	0	0	0
	Mean	0.3137	2.54×10^{-13}	0.2013	0.6115	4.2586	1.3730	0	0
	Max (worst)	1.6941	5.01×10^{-12}	1.0074	1.7147	7.7237	4.9748	0	0
	Std. dev.	0.4339	8.80×10^{-13}	0.3833	0.4815	1.5559	1.3164	0	0
F5	Min (best)	0.1132	0.0027	3.7334	1.4843	4.8953	5.32×10^{-08}	1.38×10^{-05}	8.88×10^{-16}
	Mean	0.4015	0.0451	6.5576	2.8951	6.1779	0.1715	1.28×10^{-04}	8.88×10^{-16}
	Max (worst)	1.3313	0.955	10.5058	4.7718	7.3042	1.6462	1.73×10^{-03}	8.88×10^{-16}
	Std. dev.	0.2694	0.1332	1.2746	0.599	0.5294	0.4344	2.49×10^{-04}	0
F6	Min (best)	−200.4475	−200.4475	−200.4475	−200.4471	−200.4395	−200.4475	−200.4475	−200.4475
	Mean	−200.0689	−200.4475	−198.5618	−199.9672	−199.0868	−150.7990	−197.6926	−200.4474
	Max (worst)	−181.5918	−200.4475	−181.5918	−198.2014	−193.2686	−89.8412	−181.5918	−200.4470
	Std. dev.	2.6664	1.56×10^{-12}	5.71	0.5861	1.3386	42.3979	4.6158	1.08×10^{-04}
F7	Min (best)	−18.5547	−18.5547	−18.5547	−18.5544	−18.5516	−18.5547	−18.5547	−18.5547
	Mean	−18.5521	−18.5547	−18.5547	−18.4316	−18.3571	−16.6552	−18.5547	−18.5547
	Max (worst)	−18.4758	−18.5547	−18.5547	−16.9746	−17.8192	−10.3993	−18.5547	−18.5545
	Std. dev.	0.0126	1.73×10^{-07}	1.31×10^{-07}	0.2269	0.1867	2.0012	1.79×10^{-14}	4.73×10^{-05}
F8	Min (best)	−76.2009	−80.2417	−70.9271	−87.5371	−45.7483	−76.7780	−80.574	−100
	Mean	−65.3395	−73.1429	−59.3421	−77.647	−39.1211	−65.9410	−67.848	−100
	Max (worst)	−59.7662	−67.8236	−35.7792	−71.1918	−32.0331	−61.2966	−60.995	−100
	Std. dev.	3.4832	2.8901	8.1086	3.8414	3.5161	4.2108	−60.995	0
F9	Min (best)	0	1.24×10^{-04}	3.98×10^{-12}	2.90×10^{-05}	3.60×10^{-05}	0	0	0
	Mean	9.46×10^{-10}	0.0163	8.30×10^{-03}	0.0402	0.0073	0.0161	2.02×10^{-03}	0
	Max (worst)	4.71×10^{-08}	0.0406	0.0447	0.0445	0.0265	0.0447	4.47×10^{-02}	0
	Std. dev.	6.66×10^{-09}	0.0106	1.73×10^{-02}	0.0125	0.0066	0.0217	8.86×10^{-03}	0
F10	Min (best)	4.40×10^{-04}	6.34×10^{-05}	0.9997	0.0168	0.3207	0	0.0309	0
	Mean	0.1279	0.0334	1.0004	0.0579	0.5894	0.0399	0.1502	0
	Max (worst)	0.4574	0.0456	1.0019	0.1129	0.7471	0.1229	0.3316	0
	Std. dev.	0.1069	0.0166	5.69×10^{-04}	0.0222	0.1001	0.0313	0.0574	0

proposed algorithm are obvious in cases of benchmark functions F7 and F8 where complexities of test functions are increased.

5.2. Scenario 2: practical power system problem

In order to evaluate the quality of the proposed technique for a practical problem, unit commitment as one the most important problems in operation of electric power system is assessed. This problem is a large-scale mixed integer problem (MIP) in which day-ahead power production scheduling of thermal generating units should be determined aiming at minimizing operating costs including fuel cost, start-up and shut-down costs.

This problem is subjected to some system (*e.g.* demand and reserve) and units (*e.g.* minimum on/off time, ramp up/down rates) constrains. It is noteworthy due to large scale and non-convex features of this problem; it is a costly problem from computational view point which has been investigated in many researches [44–51].

5.2.1. UC problem formulation

5.2.1.1. Objective Function. The objective function of UC problem (*UCOF*) for a generating system consisting *N* units and for *T* hours of scheduling horizon can be formulated as:

$$UCOF = \text{minimize}\,(TC) \tag{23}$$

Here:

$$TC = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[C_i\left(P_{(i,t)}.I_{(i,t)}\right) + ST_{(i,t)}.I_{(i,t)}.[1 - I_{(i,t-1)}]\right] \tag{24}$$

$I_{(i,t)}$ commitment state of unit *i* at time *t*, and fuel cost for generator *i* with fuel cost coefficients a_i, b_i and c_i is defined by Eq. (25):

$$C_i\left(P_{(i,t)}.I_{(i,t)}\right) = a_i + b_i \times P_{(i,t)} + c_i \times P_{(i,t)}{}^2 \tag{25}$$

Start-up costs can be expressed as an exponential or linear function of the time [39]. In this paper, start-up costs are modeled as a two-valued (hot start/cold start) staircase function [44]. For

Table 5
Comparison of best obtained solutions from different algorithms (unimodal function); dimension: D2.

		ABC	TLBO	ICA	BBO	GSA	PSO	DE	SRSR
F1	Min (best)	20.9616	0.0770	90.4533	2.65×10^3	202.0650	86.7748	338.26	0
	Mean	259.4144	1.2408	331.8823	4.32×10^3	300.4854	8.3405	685.04	0
	Max (worst)	1013.7	5.9629	869.7397	6.20×10^3	628.7836	493.2527	1248.9	0
	Std. dev.	248.9055	1.1920	168.0125	767.6956	65.5196	96.6024	229.03	0
F2	Min (best)	431.4416	49.0658	799.9275	1.21×10^4	7.15×10^4	156.6446	3075.6	48.5066
	Mean	8.48×10^3	49.9723	1.93×10^3	2.60×10^4	1.61×10^5	330.3673	9507.8	48.7696
	Max (worst)	1.16×10^5	52.8635	4.03×10^3	5.21×10^4	2.71×10^5	883.0405	26352	48.9163
	Std. dev.	1.77×10^4	0.8572	857.8237	8.86×10^3	4.91×10^4	151.5299	5542	0.1051
F4	Min (best)	0	24.9020	130.1062	97.1867	478.2112	65.4286	327.76	0
	Mean	61.4583	101.6300	231.9110	117.6285	520.0191	99.5531	417.87	0
	Max (worst)	252.7431	195.3031	342.9199	152.6470	553.5434	151.2542	480.95	0
	Std. dev.	85.4016	42.9534	48.3793	11.8371	17.0121	22.4923	30.229	0
F5	Min (best)	5.9047	0.0621	6.0671	8.7395	8.2637	2.7354	4.7953	8.88×10^{-16}
	Mean	9.6925	0.2186	9.3658	10.1661	9.1511	4.5972	7.6771	8.88×10^{-16}
	Max (worst)	14.6906	0.4458	17.2838	11.6550	9.7827	7.6744	20.126	8.88×10^{-16}
	Std. dev.	2.1077	0.0935	2.5389	0.5837	0.3446	1.0973	3.0628	0
F6	Min (best)	−4236.7	−4695.8	−3018.2	−4621.7	−1181.9	−2881.8	−4702.4	−4813.2
	Mean	−3845.1	−4545.1	−2529.5	−4445.5	−806.6711	−2219.7	−4473.6	−4681.6
	Max (worst)	−3490.0	4344.4	−1936.4	−4222.2	−539.5142	−1602.1	−4086.1	−4480.3
	Std. dev.	183.5911	81.2469	218.2588	79.4057	134.3862	285.28	115.3663	62.73
F8	Min (best)	−316.7334	−299.1715	−336.5846	−318.0996	−115.5267	−350.1117	−184.01	−500
	Mean	−289.7390	−276.2601	−295.9097	−298.1003	−90.9463	−331.5742	−129.29	−500
	Max (worst)	−249.4120	−249.5225	−184.8459	−281.6284	−64.5994	−317.5358	−82.62	−500
	Std. dev.	15.6372	11.4651	36.8068	7.5289	11.6338	8.5092	25.41	0
F10	Min (best)	0.0288	3.24×10^{-05}	0.0278	0.5816	0.9832	0.0031	0.1020	0
	Mean	0.1971	3.14×10^{-04}	0.870	0.7703	1.0399	0.0304	0.2985	0
	Max (worst)	0.7102	0.0012	0.1915	0.9054	1.0546	0.1073	0.8113	0
	Std. dev.	0.1194	2.34×10^{-04}	0.3888	0.0694	0.0117	0.0218	0.1604	0

Table 6
Comparison of best obtained solutions from different algorithms (unimodal function); dimension: D3.

		ABC	TLBO	ICA	BBO	GSA	PSO	DE	SRSR
F1	Min (best)	1.37×10^5	0.6033	4.18×10^4	1.50×10^5	4.88×10^3	10103	89361	0
	Mean	1.83×10^5	2.7282	5.78×10^4	1.74×10^5	8.91×10^3	15292	1.22×10^5	0
	Max (worst)	2.32×10^5	7.5115	7.91×10^4	1.93×10^5	1.39×10^4	22349	1.63×10^5	0
	Std. dev.	2.42×10^4	1.4664	8.66×10^3	9.53×10^3	1.98×10^3	2397.4	17172	0
F2	Min (best)	3.49×10^6	200.1324	5.16×10^5	4.16×10^6	4.23×10^5	41095	2.68×10^6	198.5736
	Mean	7.09×10^6	203.7160	9.23×10^5	5.13×10^6	6.40×10^5	74358	4.07×10^6	198.8343
	Max (worst)	1.06×10^7	212.1350	1.82×10^6	6.49×10^6	1.27×10^6	134610	5.79×10^6	198.8995
	Std. dev.	1.56×10^6	2.8224	2.71×10^5	4.67×10^5	1.38×10^5	18740	8.33×10^5	0.0603
F4	Min (best)	1.46×10^3	18.5455	1.34×10^3	1.48×10^3	1.90×10^3	777.6756	2345.9	0
	Mean	1.66×10^3	66.9449	1.57×10^3	1.66×10^3	2.06×10^3	896.1709	2472.8	0
	Max (worst)	1.88×10^3	143.7546	1.81×10^3	1.83×10^3	2.18×10^3	10624	2657.4	0
	Std. dev.	96.1158	29.4746	115.0177	55.7392	63.1357	65.0518	66.821	0
F5	Min (best)	18.4168	0.0860	17.2205	17.5759	10.2026	9.7014	17.137	8.88×10^{-16}
	Mean	18.9445	0.1843	18.4381	18.2013	10.9454	11.4041	18.598	8.88×10^{-16}
	Max (worst)	19.4393	0.3355	19.0665	18.6056	11.8548	12.9827	20.464	8.88×10^{-16}
	Std. dev.	0.2471	0.0639	0.3963	0.1885	0.3725	0.7696	1.1491	0
F6	Min (best)	−11743	−17852	−8871.9	−11514	−3205.6	−7705.4	−16931	−18013
	Mean	−10152	−17378	−7355.8	−10670	−2258.1	−4058.1	−15858	−17333
	Max (worst)	−9073.1	−16613	−5964.5	−10146	−1736.1	−1778.5	−14444	−16182
	Std. dev.	505.3396	226.7118	678.2347	305.3386	273.3307	1637.9	578.42	407.7910
F8	Min (best)	−957.4032	−636.7343	−668.7113	−527.6198	−489.0815	−789.6414	−112.03	−2000
	Mean	−665.9442	−472.1799	−506.2347	−423.7153	−360.1752	−874.9599	134.1	−2000
	Max (worst)	−384.3000	−337.2687	−272.9559	−345.7854	−273.9183	−10054.21	386.44	−2000
	Std. dev.	133.2749	68.1014	100.6667	44.3224	51.9544	50.7416	87.317	0
F10	Min (best)	1.3415	4.04×10^{-05}	1.0771	1.3743	1.1068	0.5447	1.2346	0
	Mean	1.5124	2.30×10^{-04}	1.1493	1.4342	1.1689	0.7379	1.3241	0
	Max (worst)	1.5947	6.02×10^{-04}	1.2056	1.4971	1.2161	0.9790	1.4589	0
	Std. dev.	0.522	1.29×10^{-04}	0.0232	0.0287	0.0173	0.0935	0.0509	0

Table 7
Optimization results obtained from different algorithms for multimodal functions.

		ABC	TLBO	ICA	BBO	GSA	SRSR
F11	Succ. times	48	49	46	40	32	50
	Mean	−1.02801	−1.03147	−1.0176	−1.0026	−0.9783	−1.03162
	Ave. optima	1.94	1.98	1.88	1.76	1.68	2
F12	Succ. times	40	43	37	35	30	47
	Mean	3.2546×10^{-6}	4.2860×10^{-7}	5.7585×10^{-6}	5.9763×10^{-5}	4.5213×10^{-3}	4.6294×10^{-8}
	Ave. optima	3.55	3.63	3.49	3.22	2.67	3.79
F13	Succ. times	32	34	29	21	18	40
	Mean	−170.8438	−173.8538	−169.5672	−165.1547	−152.2435	−175.7126
	Ave. optima	12.65	13.37	11.89	10.95	8.02	17.18
F14	Succ. times	28	29	24	21	13	34
	Mean	−178.1639	−179.2478	−175.9807	−171.2474	−163.8247	−181.5655
	Ave. optima	13.58	13.62	12.89	11.43	6.07	16.18

Table 8
The data for 10 unit case study.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P_i^{gmax}	455	455	130	130	162	80	85	55	55	55
P_i^{gmin}	150	150	20	20	25	20	25	10	10	10
a_i	1000	970	700	680	450	370	480	660	665	670
b_i	16.19	17.26	16.6	16.50	19.70	22.26	27.74	25.92	27.27	27.79
$c_i \times 10^{-2}$	0.048	0.031	0.200	0.211	0.398	0.712	0.079	0. 413	0.222	0.173
MDT_i	8	8	5	5	6	3	3	1	1	1
MUT_i	8	8	5	5	6	3	3	1	1	1
HSC_i	4500	5000	550	560	900	170	260	30	30	30
CSC_i	9000	10000	1100	1120	1800	340	520	60	60	60
CSH_i	5	5	4	4	4	2	2	0	0	0
Ini. S_i	8	8	−5	−5	−6	−3	−3	−2	−1	−1

unit i with hot start-up cost (HSC_i) and cold start-up (CSC_i), time-dependent cost of start-up is defined by Eq. (26) [44]:

$$ST_{(i,t)} = \begin{cases} HSC_i, \text{if} MDT_i \le DT_i \le MDT_i + CSH_i \\ CSC_i, \text{if} DT_i > MDT_i + CSH_i \end{cases} \tag{26}$$

MDT_i is minimum down-time limit of unit i, CSH_i is cold start hour of unit i, and DT_i is the unit's down time. Similarly, Shutdown cost can be considered as a fix, staircase or exponential cost for each unit per shut down. However, in this paper, the shut-down cost of units is not considered during simulation procedure.

5.2.1.2. Constraints. The PBUC problem is formulated subject to following system and unit constraints [46].

A. Unit constraints

1 Unit generation limits

$$P_{(i)}^{\text{gmin}} \le P_{(i,t)} I_{(i,t)} \le P_{(i)}^{\text{gmax}} \tag{27}$$

Power production of units is constrained to minimum and maximum limits of $P_{(i)}^{\text{gmin}}$ and $P_{(i)}^{\text{gmax}}$, respectively.

2 Ramp up/down rates

By considering ramp up/down rates constrains, difference of values in production levels is limited to a maximum value in consecutive periods of scheduling horizon. For generator i with the ramp-up RU_i and ramp-down RD_i, this constrain is formulated by Eqs. (28) and (29):

When generator ramps up:

$$P_{(i,t)} = \min\left\{P_{(i)}^{\text{gmax}}, P_{(i,t-1)} + \varphi \times RU_i\right\} \tag{28}$$

When generator ramps down:

$$P_{(i,t)} = \max\left\{P_{(i)}^{\text{gmin}}, P_{(i,t-1)} - \varphi \times RD_i\right\} \tag{29}$$

φ is equal to 60 min and it is the UC time step.

3 Unit minimum ON/OFF durations

This constrain limits minimum duration of *ON* status of generator operation before shutting the unit down as well as minimum hours that should be spent on *OFF* status before next start up. This constrain can be formulated by Eq. (30):

$$\begin{cases} \bar{X}_i^c \ge MUT_i \text{ if} \bar{X}_i^c \ge 0 \\ -\bar{X}_i^c \ge MDT_i \text{ if} \bar{X}_i^c < 0 \end{cases} \tag{30}$$

MUT_i is minimum up-time limit of unit i, and $\bar{X}_i^c$ is a signed integer which represents the continuous *ON*/*OFF* status duration of the ith cycle of the ith unit. The sum of the absolute values of $\bar{X}_i^c$ for all units must be equal to the scheduling horizon.

B. System constraints

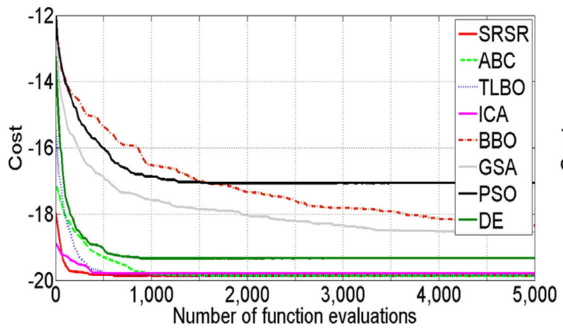
1 Demand constraint

$$\sum_{i=1}^{N} P_{(i,t)}.I_{(i,t)} = P_{D(t)} t = 1, \ldots, T \tag{31}$$

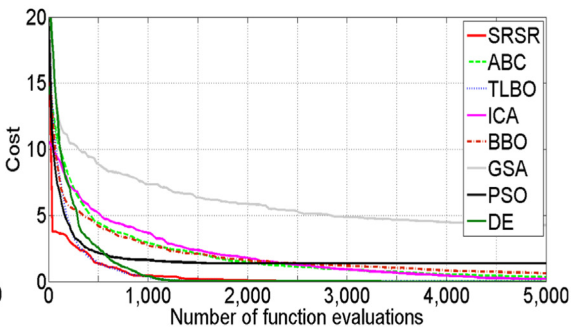
$P_{D(t)}$ is system load demand at hour t.

2 Spinning reserve of the system

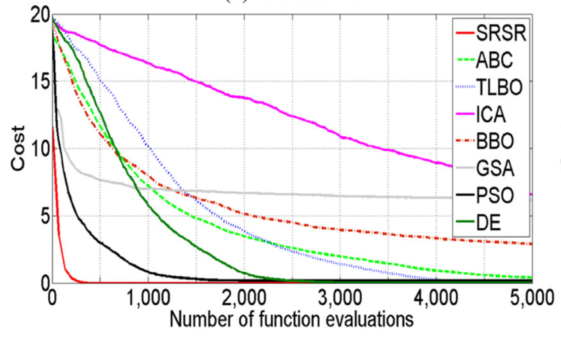
$$\sum_{i=1}^{N} \bar{P}_{(i,t)}.I_{(i,t)} = P_{D(t)} + P_{R(t)} t = 1, \ldots, T \tag{32}$$



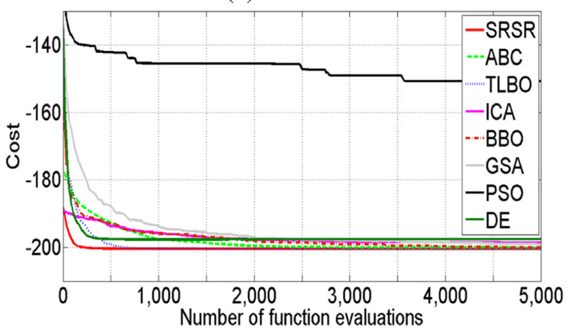
(c) Function F3



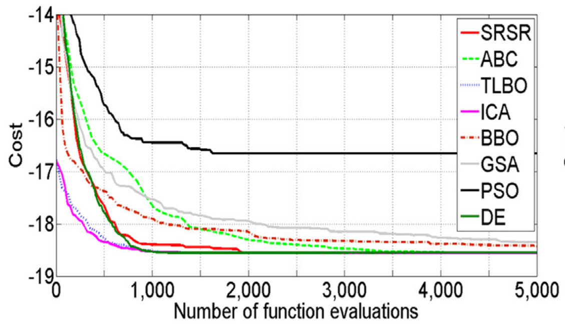
(d) Function F4



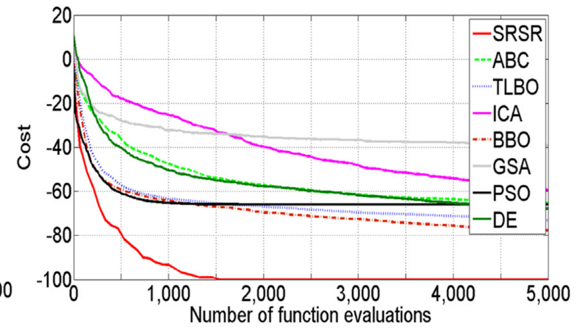
(e) Function F5



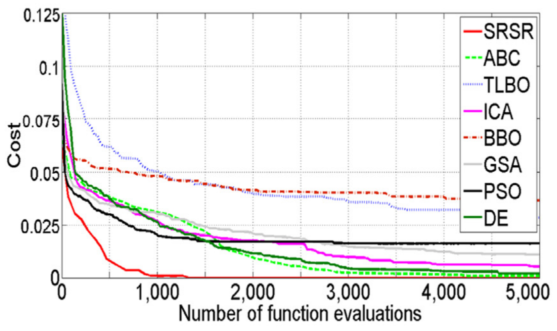
(f) Function F6



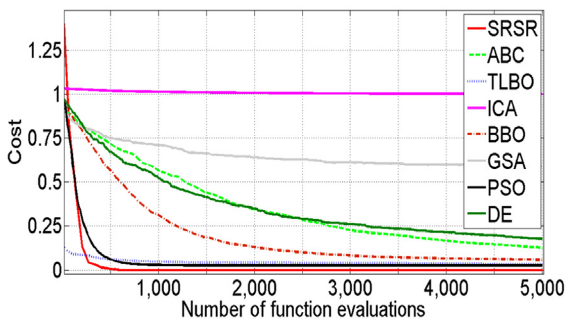
(g) Function F7



(h) Function F8



(i) Function F9



(j) Function F10

Fig. 7. Algorithms' convergence *versus* NFE for functions F1–F10.

Table 9
Hourly forecasted load and power price in power market.

Hour [h]	1	2	3	4	5	6	7	8	9	10	11	12
Load [MW]	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Hour [h]	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Load [MW]	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

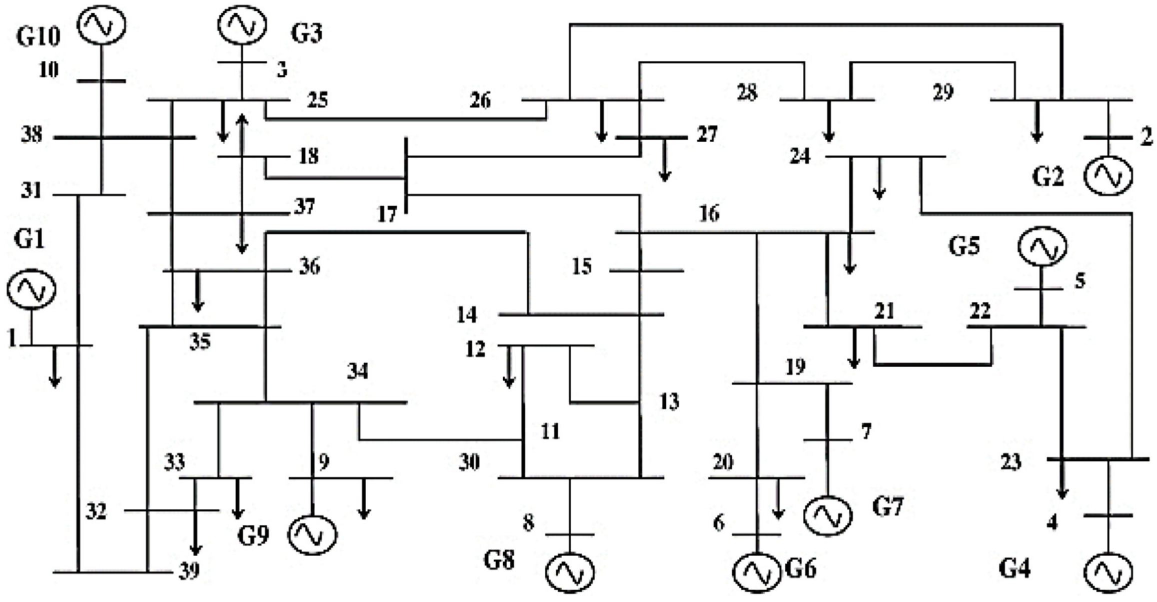


Fig. 8. Single line diagram of IEEE 39 bus system.

Table 10
Power dispatch for 10 unit system using SRSR.

Time [h]	Load [MW]	U1 [MW]	U2 [MW]	U3 [MW]	U4 [MW]	U5 [MW]	U6 [MW]	U7 [MW]	U8 [MW]	U9 [MW]	U10 [MW]	Reserve [% Load]
1	700	455	245	0	0	0	0	0	0	0	0	30.00
2	750	455	295	0	0	0	0	0	0	0	0	21.33
3	850	455	370	0	0	25	0	0	0	0	0	26.12
4	950	455	455	0	0	40	0	0	0	0	0	12.84
5	1000	455	390	0	130	25	0	0	0	0	0	20.20
6	1100	455	360	130	130	25	0	0	0	0	0	21.09
7	1150	455	410	130	130	25	0	0	0	0	0	15.83
8	1200	455	455	130	130	30	0	0	0	0	0	11.00
9	1300	455	455	130	130	85	20	25	0	0	0	15.15
10	1400	455	455	130	130	162	32	26	10	0	0	10.86
11	1450	455	455	130	130	162	44	54	10	10	0	10.83
12	1500	455	455	130	130	162	53	85	10	10	10	10.80
13	1400	455	455	130	130	162	32	26	10	0	0	10.86
14	1300	455	455	130	130	85	20	25	0	0	0	15.15
15	1200	455	455	130	130	30	0	0	0	0	0	11.00
16	1050	455	310	130	130	25	0	0	0	0	0	26.86
17	1000	455	260	130	130	25	0	0	0	0	0	33.20
18	1100	455	360	130	130	25	0	0	0	0	0	21.09
19	1200	455	455	130	130	30	0	0	0	0	0	11.00
20	1400	455	455	130	130	162	32	26	10	0	0	10.86
21	1300	455	455	130	130	85	20	25	0	0	0	15.15
22	1100	455	455	0	0	145	20	25	0	0	0	12.45
23	900	455	425	0	0	0	20	0	0	0	0	10.00
24	700	455	345	0	0	0	0	0	0	0	0	13.75

Table 11
Commitment status for 20 unit system using SRSR.

Time [h]	ON Units	Reserve [% Load]	Time [h]	ON Units	Reserve [% Load]
1	1–4	30.00	13	1–16	10.86
2	1–4	21.33	14	1–13	11.88
3	1–4, 10	16.59	15	1–10	11.00
4	1–4, 9, 10	12.84	16	1–4, 6–10	20.67
5	1–4, 7, 9, 10	13.70	17	1–4, 6–10	26.70
6	1–5, 7–10	15.18	18	1–4, 6–10	15.18
7	1–5, 7–10	10.17	19	1–4, 6–10, 12, 14	12.46
8	1–10	11.00	20	1–4, 6–18	10.14
9	1–13	11.88	21	1–4, 6–14	10.15
10	1–16	10.86	22	1–4, 8–11, 13	10.86
11	1–18	10.83	23	1–4, 10	10.11
12	1–20	10.80	24	1–4	13.75

Table 12
Commitment status for 40 unit system using SRSR.

Time [h]	ON Units	Reserve [% Load]	Time [h]	ON Units	Reserve [% Load]
1	1–8	30.00	13	1–32	10.86
2	1–8	21.33	14	1–24, 28	10.25
3	1–8, 20	11.82	15	1–8, 11, 13–24, 28	11.31
4	1–8, 15, 17, 18, 20	12.00	16	1–8, 11, 13–20	17.57
5	1–8, 15–20	13.70	17	1–8, 11, 13–20	23.45
6	1–8, 12–20	12.23	18	1–8, 11, 13–20	12.23
7	1–8, 10, 12–20	10.17	19	1–8, 11, 13–24, 27	11.31
8	1–20	11.00	20	1–24, 27, 29–36	10.23
9	1–24, 27	10.25	21	1–24, 27	10.25
10	1–32	10.86	22	1–10, 12, 14, 16, 18–20, 24	10.36
11	1–36	10.83	23	1–10, 12	11.94
12	1–40	10.80	24	1–7, 9, 10, 12	11.72

Table 13
Commitment status for 60 unit system using SRSR.

Time [h]	ON Units	Reserve [% Load]	Time [h]	ON Units	Reserve [% Load]
1	1–12	30.00	13	1–43, 45–48	10.20
2	1–12	21.33	14	1–16, 18–36, 38, 39, 41	10.22
3	1–12, 29	10.24	15	1–12, 15, 16, 19–36	10.44
4	1–12, 25–29	10.00	16	1–12, 15, 16, 19–30	18.60
5	1–12, 21, 23–30	13.70	17	1–12, 15, 16, 19–30	24.53
6	1–12, 17, 19–30	11.24	18	1–12, 15, 16, 19–30	13.21
7	1–12, 14, 17–30	10.17	19	1–12, 15–17, 19–31, 35, 39, 41	10.17
8	1–30	11.00	20	1–36, 39, 41, 43–52, 54	10.08
9	1–37, 41	10.79	21	1–36, 39, 41	10.79
10	1–46, 48	10.20	22	1–14, 17, 18, 20, 22–24, 26, 28, 29, 32–34, 36	10.70
11	1–52, 54	10.20	23	1–14, 17, 18	10.74
12	1–59	10.19	24	1–7, 9–14, 18	12.40

Table 14
Commitment status for 80 unit system using SRSR.

Time [h]	ON Units	Reserve [% Load]	Time [h]	ON Units	Reserve [% Load]
1	1–16	30.00	13	1–58, 60–64	10.37
2	1–16	21.33	14	1–16, 18, 20–48, 52–56	10.20
3	1–16, 35, 38	11.82	15	1–16, 20, 21, 23, 25–45, 47, 48	10.06
4	1–16, 29, 34–36, 38–40	10.29	16	1–16, 20, 21, 23, 25–40	19.12
5	1–16, 25, 26, 28, 29, 33–40	13.70	17	1–16, 20, 21, 23, 25–40	25.08
6	1–16, 23, 25–40	10.75	18	1–16, 20, 21, 23, 25–40	13.70
7	1–17, 22–40	10.17	19	1–17, 19–21, 23, 25–40, 47, 48, 51, 53	10.38
8	1–40	11.00	20	1–48, 51, 53, 57–72	10.23
9	1–48, 50, 54	10.25	21	1–48, 51, 53	10.25
10	1–63	10.37	22	1–19, 22, 24–26, 30–33, 36, 37, 39, 41–46	10.32
11	1–66, 68–72	10.35	23	1–19, 22, 24	10.14
12	1–74, 76–80	10.34	24	1–9, 11–16, 18, 22, 24	12.73

Table 15
Commitment status for 100 unit system using SRSR.

Time [h]	ON Units	Reserve [% Load]	Time [h]	ON Units	Reserve [% Load]
1	1–20	30.00	13	1–70, 72, 74–80	10.07
2	1–20	21.33	14	1–52, 55–60, 62, 66, 68, 70	10.00
3	1–20, 44, 46	10.87	15	1–22, 26–28, 31–52, 55–57, 59, 60	10.25
4	1–20, 35, 37, 41, 44, 46–50	10.46	16	1–22, 26–28, 31–50	20.67
5	1–20, 32, 35–38, 41–50	13.70	17	1–22, 26–28, 31–50	26.70
6	1–21, 31–50	10.45	18	1–22, 26–28, 31–50	15.18
7	1–22, 24, 29–50	10.17	19	1–22, 26–28, 31–50, 52–55, 62, 63, 68	10.37
8	1–50	11.00	20	1–60, 62, 63, 68, 71–86, 88–90	10.14
9	1–53, 55, 57–60, 65, 66, 68, 70	10.00	21	1–60, 62, 63, 68	10.58
10	1–76, 79, 80	10.07	22	1–20, 23–25, 29–33, 36–38, 40–44, 46, 50, 51, 56–60	10.11
11	1–83, 85–89	10.07	23	1–20, 23–25, 29, 30, 41	10.13
12	1–92, 94–98, 100	10.07	24	1–12, 14–18, 20, 23–25, 29, 30	10.50

Table 16
Hourly operation cost of 10, 20, 40, 60, 80 and 100 unit systems.

Time [h]	Number of generating units					
	10	20	40	60	80	100
1	13,683.13	27,366.71	54,733.45	82100.23	109,467.03	136,833.86
2	14,554.50	29,109.33	58,218.79	87328.40	116,438.15	145,547.50
3	17,709.45	34,011.32	66,615.07	99218.83	133,230.42	165,834.15
4	18,597.67	38,096.56	76,680.05	114,745.19	152,316.56	190,875.63
5	20,580.02	40,017.23	80,374.47	120,951.70	161,308.93	201,666.17
6	23,487.04	46,378.28	91,066.97	135,905.90	180,743.83	225,582.95
7	23,261.98	46,009.27	93,119.81	140,229.34	187,339.66	234,449.45
8	24,150.34	49,400.88	98,802.56	148,204.46	197,605.55	247,007.43
9	27,986.06	54,914.53	108,771.65	163,687.05	217,544.78	272,019.09
10	29,992.61	60,505.22	121,530.44	181,283.95	242,309.18	302,222.69
11	31,842.63	63,685.31	127,370.62	190,346.28	254,031.62	317,007.28
12	33,705.61	67,411.34	134,823.19	201,516.21	268,927.89	335,621.13
13	29,932.61	59,865.22	119,730.44	178,903.95	238,769.18	297,942.69
14	27,126.06	53,714.53	106,891.65	160,926.34	214,964.13	267,219.09
15	24,150.34	48,300.88	98,012.22	146,328.39	194,774.02	243,043.57
16	21,513.66	42,407.15	84,198.06	126,603.94	169,010.71	212,036.98
17	20,641.82	40,659.26	80,698.79	121,357.68	162,016.74	203,297.19
18	22,387.04	44,158.28	87,726.97	131,860.95	176,019.24	220,791.42
19	24,150.34	49,415.52	98,952.22	147,412.07	196,253.02	244,890.84
20	30,422.61	62,028.61	123,262.92	184,218.94	245,895.97	307,272.21
21	27,126.06	54,044.05	106,891.65	160,607.05	213,784.78	267,499.34
22	22,610.52	44,456.61	87,762.31	132,272.91	176,276.93	219,994.65
23	17,645.36	34,862.82	70,560.61	105,531.35	140,502.59	175,362.51
24	15,427.42	30,854.93	62,637.38	93,492.18	124,347.33	155,510.67
Total	56,2684.87	1,121,673.83	2,239,432.31	3,355,033.29	4,473,878.23	5,589,528.49

Table 17
Comparison of operation cost obtained by SRSR and other algorithms for different case studies.

No. of units	Total operation cost of generating units							
	LR [47]	ICGA [44]	DE [48]	BF [49]	ICA [46]	SFL [50]	GMTLBO–BH [51]	SRSR
10	565,825	566,404	566,070	564,842	564,405	564,769	563,937	562,684
20	1,130,660	1,127,244	1,126,121	1,124,892	1,124,274	1,123,261	1,123,297	1,121,673
40	2,258,503	2,254,123	2,255,077	2,246,223	2,247,078	2,246,005	2,245,601	2,239,432
60	3,394,066	3,378,108	–	3,369,237	3,379,120	3,368,257	–	3,355,033
80	4,526,022	4,498,943	–	4,491,287	4,508,762	4,503,928	–	4,473,878
100	5,657,277	5,630,838	–	5,611,514	5,617,913	5,624,526	5,611,105	5,589,528

$P_{R(t)}$ is system reserve at hour t. $\bar{P}_{(i,t)}$ should be obtained by (28) and (29) with $\varphi = 10$ min. This is 10-min maximum response-rate-constrained active power of generating unit i.

Obviously, economic load dispatch (ELD) should be executed in order to reach optimal power of each generating unit after determining commitment status of units. Traditional ELD has been employed to specify power dispatched during scheduling horizon.

5.2.2. *Case study*

The proposed SRSR algorithm has been applied to systems with 10, 20, 40, 60, 80, and 100 generating units for a 24-h scheduling time horizon with one period per hour. Data for the generation system consisting 10 units is detailed in Table 8. The data for forecasted load is given in Table 9 [45]. Single line diagram of the IEEE 39 bus system with ten generation units is shown in Fig. 8. Method of MIP codification of solutions is based on [45].

For the 20-generating unit system, the data of the ten generating unit system duplicated and the load data multiplied by 2. Similarly, data for 10 unit system and respective load demand scaled appropriately in order to provide data for larger-scale test systems. 10% of hourly load demand of system is considered as spinning reserve of generation in all cases. Optimum power dispatched corresponding to the best solution obtained by SRSR for the given 10-unit system and commitment status of generating units for 20, 40, 60, 80 and 100 unit system are shown in Tables 10–15. Operation costs corresponding to the obtained solutions for the given test systems are detailed in Table 16.The results obtained by SRSR have been compared with other methods in Table 17 for 6 given generating systems. It can be seen, with the increment of scale of test systems, hourly reserve constrains are satisfied marginally. In other words, changes in size of case studies donate algorithm freedom to search marginal points more precisely. Optimal parameters of the proposed algorithm have been obtained through several runs of program. Obviously, number of initial solutions should be proportionally increased along with increment of generating system scale. Needless to say, a trade-off should be placed between the number of initial solutions and optimality of results as a further increase in the number of solutions may cause algorithm to incur higher computational costs; while, convergence may not improve as expected. Effectiveness of proposed SRSR algorithm in term of optimality of obtained solutions (lower operation cost of generating systems) has been validated by comparison of the results as detailed in Table 17.

6. Conclusion

In this paper, a novel algorithm called SRSR has been proposed based on collective search approach of a swarm of robots to find a victim in post-disaster locations. In contrast to previously nature-inspired optimization algorithms, collective intelligence in artificial life is the main inspiration of the presented method. A set of problems including several standard benchmark functions and a practical electric power system problem have been utilized to assess the performance of the presented optimization algorithm in terms of quality solutions as well as convergence pace. However, quality of the solutions obtained by SRSR surpasses those of other algorithms in almost all the cases; obviously, it is not possible to conclude that the proposed algorithm is universally superior to all other previously proposed population-based methods. In fact, the acceptable performance of SRSR in cases of benchmark functions and UC problem provides some evidences that this algorithm can be successfully applied to other challengeable optimization problems in different branches of science. Finally, authors proposed some research directions for future works as follows:

i Considering eye-catching role of mean and variance factors of distribution function on convergence of algorithm, a novel method for updating these factors can ameliorate algorithm performance.
ii However normal PDF has shown an acceptable performance about presented problems, utilizing of other PDFs like Gamma and Pareto during ending iterations of algorithm can improve convergence pace.
iii However, authors defined movement factor as distance between best and worst solutions, a more targeted calculation method of this factor can advance quality of second operator and subsequently overall performance of optimization algorithm.
iv The functions *round* and *exponent* can be categorized as basic operators that have never been utilized separately to improve and also accelerate performance of any optimization algorithm. Employing similar operators my assist algorithm to reach a better quality.

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