Kawambwa and Mnyanghwalo
Journal of Electrical Systems and Inf Technol (2023) 10:6
https://doi.org/10.1186/s43067-023-00072-7

Journal of Electrical Systems
and Information Technology

RESEARCH **Open Access**

A multi-agent-based symbiotic organism search algorithm for DG coordination in electrical distribution networks

Shamte Kawambwa[1*] and Daudi Mnyanghwalo[2]

*Correspondence:
kawambwa.shamte@udsm.ac.tz;
shamtej2@gmail.com

[1] Department of Electronics and Telecommunications Engineering, University of Dar es Salaam, Dar es Salaam, Tanzania
[2] Department of Computer Science and Engineering, University of Dar es Salaam, Dar es Salaam, Tanzania

Abstract

Metaheuristic algorithms have become popular in solving engineering optimization problems due to their advantages of simple implementation and the ability to find near-optimal solutions for complex and large-scale problems. However, most applications of metaheuristic algorithms consider centralized design, assuming that all possible solutions are available in one machine or controller. In some applications, such as power systems, especially DG coordination, centralized design may not be efficient. This work integrates a multi-agent system (MAS) into a metaheuristic algorithm for enhanced performance. In a proposed multi-agent framework, the agent implements a metaheuristic algorithm and uses shared information with neighbours as input to optimize the solutions. In this study, a new distributed Symbiotic Organism Search (SOS) algorithm has been proposed and tested in the proposed multi-agent framework. The proposed algorithm is termed a multi-agent-based symbiotic organism search algorithm (MASOS). The MASOS has been tested and compared with other proficient algorithms through statistical analysis using benchmark functions. The results show that the proposed MASOS solves the considered benchmark functions efficiently. Then MASOS was tested for DGs coordination considering load variations in the Tanzanian electrical distribution network. The results show that the coordination of DG using the proposed algorithm reduces power loss and improves the voltage profiles of the power system.

Keywords: Metaheuristic, Multi-agent, Symbiotic organism search, DG coordination, Electrical distribution network

Introduction

In power distribution systems, emerging technologies such as active distribution networks, group microgrid control, DG units, controllable loads and electric vehicles enable power distribution networks to present more stochastic operation conditions rather than deterministic one [1]. The increasing usage of sophisticated electronic equipment in industrial, residential and commercial sectors introduces stochastic behaviour that cannot readily be eliminated from utility systems. However, the inclusion of the DG in the electrical distribution systems can mitigate many problems associated with the stochastic nature of the load. Such advantages of DGs have increased the attention of many

© The Author(s) 2023. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

researchers in proposing methods for integrating the DGs in the distribution networks [2–4]. Bokhari, et al. [5] found that a small percentage of DGs installed in the distribution network can alleviate voltage violation and allow electric utilities to use deeper voltage reduction during critical conditions. Despite the advantages, the DGs are associated with an uncertainty nature which also introduces stochastic behaviour in the distribution network [6].

Resource coordination can achieve efficient system performance in such dynamic operating conditions. DGs coordination in the distribution system is a large-scale dynamic optimization problem with fast-varying system conditions [1]. In power systems, centralized and distributed techniques have been applied in coordinating resources such as DG, loads, electric vehicles, microgrids, and overcurrent relays [7–9]. Several researchers have reported the coordination of DGs, such as solar photovoltaic and electric vehicle chargers, in the distribution networks [2, 10, 11]. Kotsalos, et al. [2] proposed a framework for coordinating multiple DGs in low voltage networks to mitigate overvoltage and minimize active power curtailment. Cheng et al. [11] proposed a distributed coordination strategy of solar photovoltaic in low voltage to deal with voltage fluctuation issues. Wang, et al. [10] proposed a bi-level voltage control scheme for coordinating electric vehicle chargers in low voltage networks using a higher-level consensus algorithm and a localized power allocator at the lower level. However, most of these studies involve bi-level control in which the upper level is centralized. The centralized control approaches may encounter computation and communication bottlenecks in handling such a large-scale optimization problem in the electrical distribution network.

Distributed control algorithms have many advantages over centralized algorithms due to their ability to handle large-scale complex optimization problems [12]. Multi-agent System (MAS) is one of the popular techniques for implementing distributed control algorithms. In MAS, multiple agents interact, and use the shared information and defined algorithm to solve a common problem cooperatively. Several techniques based on distributed optimization methods have been proposed for coordinating power system operations, such as consensus-based, decomposition based and metaheuristic based [13]. In consensus-based algorithms, control agents share variables of interest and try to synchronize to reach a common agreement [14, 15]. The consensus algorithms are very popular and have been used many times in coordinating power systems operations [16–19]. The decomposition-based control involves breaking the complex problems into simpler subproblems and applying the alternating direction method of multipliers (ADMM) [13]. The applications of decomposition methods in power systems have been presented [20, 21]. Due to its simple implementation, the consensus-based approach is more popular than its counterpart ADMM approach. In the metaheuristic approach, agents cooperate with neighbours to implement a specific metaheuristic algorithm that optimizes a given problem [22, 23].

Metaheuristic algorithms are among efficient techniques for solving complex and large optimization problems, including power system problems [24, 25]. Most of the metaheuristic algorithms are designed to operate in a centralized control framework, limiting their use in some applications that need distributed frameworks. In order to design metaheuristic algorithms that operate in distributed systems, studies which integrate multi-agent systems (MAS) and metaheuristic algorithms have emerged and applied to solve different real-world optimization problems. Multi-Agent Genetic Algorithm (MAGA), which integrates MAS and genetic algorithms for optimizing linear systems, was presented by Zhong et al. [22]. A multi-agent quantum evolutionary algorithm for solving global numerical problems was proposed [26]. A Multi-Agent-based Particle swarm optimization (MAPSO) for solving reactive power dispatch problems in transmission systems was proposed by Bokhari, et al. [27]. Acharya and Mishra [23] proposed a multi-agent-based Symbiotic organism Search algorithm for tuning fractional order PID Controller. The studies for metaheuristic algorithms integrated with MAS, reported by authors in [22, 23, 26, 27] involves a lattice-like neighbourhood whereby an agent interacts with only directly connected neighbours. The studies assume a centralized program that initializes and controls interaction among agents. The centralized program assumes a shared memory which enables agents to access the states of neighbours. In such settings, algorithm operations for one agent may directly modify the state of neighbours, which is not the case for real-life systems. In distributed control paradigm and real-life multi-agent systems, each agent operates independently and interacts with neighbours through messaging. In such cases, the reviewed studies for multi-agent-based solutions may not be efficient.

Therefore, this study proposes a distributed multi-agent-based framework to enable the implementation of a metaheuristic algorithm in solving optimization problems in a distributed manner. The proposed multi-agent framework can accommodate many metaheuristic algorithms, including symbiotic organism search (SOS) [28], particle swarm optimization (PSO) [29], teaching learning-based optimization (TLBO) [30], and whale optimization algorithm (WOA) [31], just to mention few. In this work, the SOS algorithm reported by Cheng and Prayogo [28] has been implemented in the proposed framework to form a newly proposed algorithm termed Multi-Agent-based Symbiotic Organism Search (MASOS). The SOS is one of the algorithms with good features such as simple implementation, simple computational, good convergence and parameter independence. A study by authors in [32] found SOS to have the best average CPU time for different problem dimensions. SOS and its variants have been used for several engineering applications, including DG placements in radial distribution networks [33–37]. Also, SOS has been used for solving network reconfiguration with DGs and capacitor placement [38–40]. It should be noted that the differences between the proposed MASOS in this study and that proposed by Acharya and Mishra [23] lie in the design, agent interactions and implementations of the algorithm.

The performance of the proposed MASOS algorithm in solving optimization problems has been tested through statistical analysis using ten benchmark functions. In all tested functions, the proposed algorithm has been compared with the original SOS and other algorithms. The comparative results have proved the superiority of the proposed MASOS in solving such benchmark functions. In testing the performance of the proposed algorithm in solving engineering optimization problems, the MASOS has been applied in coordinating DG in the electrical distribution networks considering load variations. The results show that the proposed MASOS algorithm has provided competitive performances with the added advantage of running in a distributed framework.

The major contribution of this paper can be summarised as (i) A generalized multi-agent-based framework for implementing metaheuristic algorithms has been proposed (ii) The

DG coordination framework that involves multi-agent and metaheuristic algorithms for solving power loss optimization problems considering load variations has been proposed. (iii) Integration of MAS and SOS algorithm exploits the good features of distributed control systems and the ability of SOS algorithms to solve complex problems resulting in a robust control systems (iv) Unlike other versions of SOS and other versions of distributed multi-agent-based metaheuristic algorithms which involves memory sharing the proposed MASOS is purely distributed such that each agent runs independently.

The rest of this paper is organized as follows. The "Mathematical Problem Formulation" section presents objective functions and constraints. The "Methods" section describes the theoretical background of the multi-agent system, metaheuristic algorithm, proposed multi-agent framework, and proposed MASOS algorithm. The "Results and discussion" section presents results and discussion for considered benchmark functions and compares the performance of the MASOS and other algorithms. It also presents the performance of the proposed MASOS in coordinating the DGs in the electrical distribution networks. The "Conclusion" section concludes this paper and highlights the areas for future work.

Mathematical problem formulation

Load variations in the electrical system change operation variables such as power loss, voltage profile, voltage deviation and operation costs. Studies indicated that optimizing real power loss as an objective function reduces real power loss and improves the entire power system performance parameters [41]. Therefore, in this study, active power loss and voltage deviations have been considered as the objective function to be minimized.

Objective functions

In a radial distribution system, the active power loss is more influential than reactive power loss. The optimization methods aim to minimize the power loss and voltage deviation from the rated voltage values of the power systems [42]. The objective function for power loss and voltage deviations is presented in (1) and (2), respectively. In evaluating the efficacy of the possible solutions, power flow is run to get power system variables. In this study, the Direct Load Flow (DLF) [43] method was used due to its high computational efficiency.

$$P_{\text{loss}} = \sum_{i=1}^{nb} I_i^2 * R_i \tag{1}$$

$$V_d = \sum_{k=1}^{n} (V_k - V_{\text{rated}})^2 \tag{2}$$

where P_{loss} is the total power loss I_i is the current through the branch i , and R_i the resistance of branch i and nb is the number of buses. V_k is the voltage magnitude of the k^{th} bus, expressed in p.u and V_{rated} is the rated voltage of the network, which is 1 p.u. and V_d is the overall voltage deviation of the network.

Constraints

The node voltage for each bus and for each possible solution is given in (3)

$$V_{\min} < V_i < V_{\max} \text{ where } i = 1, 2, 3, \ldots, n \tag{3}$$

where V_i is the voltage magnitude of k^{th} bus, $V_{\max}$ is the upper voltage limit and $V_{\min}$ is lower voltage limit. In this work, the minimum and maximum voltage limits are 0.9 p.u and 1.1 p.u, respectively. The values of voltage limits are according to the Tanzania electrical power system.

Methods

Basic structure of metaheuristic algorithms

The basic structure of most metaheuristic algorithms consists of an outer loop and an inner loop, as shown in Algorithm 1 of Appendix. The outer loop usually represents the number of times the algorithm repeats itself before satisfying termination criteria. The number of times the algorithm uses to achieve a solution for a given problem is among many other criteria for metaheuristic algorithms evaluation. The fewer number of times, the better the algorithm. The inner loop represents the execution of the mathematical and logical formulation of a particular metaheuristic algorithm for each member of the population. The number of times the inner loop executes is equal to the size of the population. The mathematical formulation of the inner loop is the core part which defines the interaction between members in the population/swarm. The inner loop determines the characteristics and performance parameters of metaheuristic algorithms, such as convergence, complexity, accuracy, and exploration.

In a metaheuristic algorithm, each member of the population can find its solution in consensus with others. Most of the algorithm's applications involve the implementation of centralized cooperation among members of the population. In such implementations, a centralized application implements the properties of members, and in most cases, members exchange information through shared memory or a central controller. In some applications involving distributed control, such implementation technique may not be feasible, limiting the applicability of algorithms in solving complex problems. Although most algorithm designs follow the structure presented in Algorithm 1 of Appendix, the interaction among members and quality of solutions are different for different metaheuristic algorithms. Therefore, this work proposes the framework to enable distributed implementation of metaheuristic algorithms and implement the Symbiotic organism search algorithm in multi-agent.

Proposed multi-agent-based metaheuristic algorithms framework

In Multi-Agent System (MAS) agents achieve their goals through cooperation and competition with or without sharing their knowledge [44]. The agent can sense, communicate and interact with neighbour agents to take actions in response to changes occurring in the environment without external intervention from other agents or humans [23]. Therefore, this work proposes a framework for implementing metaheuristic algorithms in a Multi-agent system following the structure presented in Algorithm 1. In the proposed framework, each member of the population/swarm in the metaheuristic algorithm is implemented as a MAS agent. Each agent shares its current states with neighbours and runs a metaheuristic algorithm to update its current state. Unlike the centralized implementation of metaheuristic algorithms, which involves memory sharing, and the central controller that can access the information of the current global solution at each stage, in a distributed framework, agents only share their states, and the current global solution is not known. This fact may bring about the diversity among different algorithms implemented using this framework since there are some algorithms whose convergence characteristics and solution quality are highly dependent on global value. The generalized execution steps for each agent are presented in Fig. 1.

Initialization

Agent initialize its states using (4) and evaluate its initial fitness

$$X_i^0 = X_i^l + r * (X_i^u - X_i^l) \tag{4}$$

where X_i^0 is the initial solution of dimension i,X_i^l is lower bound of dimension i ,X_i^u is upper bound of dimension i, r is random value within uniform distribution $r \in (0, 1)$.

Local neighbourhood identification

Each agent identifies local neighbours who can be socializing with. The local neighbourhood definition depends on the structure of the problem and influences the performance of the algorithms.

Socialization

Socialization involves sharing the states between neighbouring agents. Socialization involves two stages, sending own states and receiving states from neighbours. Upon receiving the states of all its neighbours, agents formulate the population.

Solution state updates

From the population formulated in the socialization stage, the agent updates its states using the inner loop of the corresponding metaheuristic algorithm.

Considering the generalized structure of the Metaheuristic algorithm presented in Algorithm 1 of Appendix, in the proposed framework, the outer loop is presented as

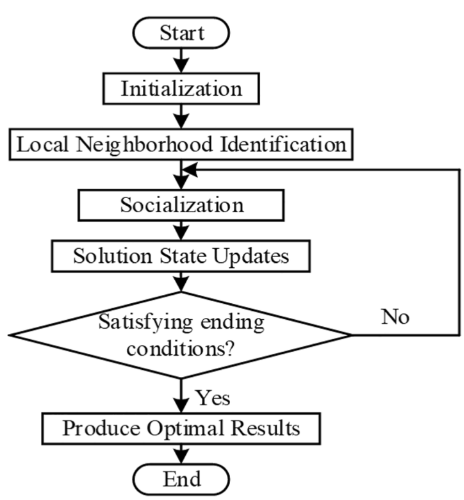

Fig. 1 A proposed framework for multi-agent-based metaheuristic algorithms

the number of times agents exchange information and the inner loop is presented as the steps performed by agents to run the inner loop of the corresponding metaheuristic algorithm as presented in Fig. 1. Based on this framework and assumptions made, implementation of the centrally designed metaheuristic algorithm may change and may be different for different algorithms. In order to test the validity of the proposed framework, the multi-agent-based SOS has been designed and implemented.

The symbiotic organism search algorithm

The Symbiotic Organism Search algorithm is a metaheuristic algorithm inspired by the biological relationship among organisms in the ecosystem. The conventional SOS involves three major phases: mutualism, commensalism, and parasitism. The basic structure of SOS is presented in Algorithm 2 of Appendix, and more details of convention SOS can be found in [28].

Mutualism

In the mutualism phase, the two interacting organisms benefit and enhance their chance of survival. If X_i and X_j are two interacting organisms, the new candidate solutions X_{inew} and X_{jnew} is generated using (5) and (6). The mutualism phase determines the exploitation capability and ensures convergence of the algorithms to the global optimal.

$$X_{\text{inew}} = X_i + R * (X_{\text{best}} - \text{MV} * BFi) \tag{5}$$

$$X_{\text{jnew}} = X_j + R * (X_{\text{best}} - \text{MV} * BFi) \tag{6}$$

where

$$\text{MV} = \frac{X_i + X_j}{2} \text{and } R = \text{rand}(0,1)$$

The BF_i and BF_j are randomly selected as 1 or 2 which represents the benefit level for organism X_i and X_j, respectively. The MV is mutual vector which represents the relationship between organism X_i and X_j . The X_{best} represents the organism with the best objective function in the solution space.

Commensalism

In the commensalism phase, two organisms X_i and X_j interact such that one organism benefits while the other organism neither benefits nor suffers. That is X_i increases its chance of survival in the ecosystem by benefiting from X_j. The new candidate solution for X_i is given in (7). The commensalism phase determines the direction of search space and balances exploration and exploitation ability of the algorithm.

$$X_{\text{inew}} = X_i + \text{rand}(-1,1) * (X_{\text{best}} - X_j) \tag{7}$$

Parasitism

In the parasitism phase, two organisms X_i and X_j interact such that one organism benefits while another organism suffers. The parasite for the randomly selected organism X_j called X_{jpar} is formed from a randomly selected organism X_i using (8). The parasitism phase ensures the exploration of the algorithm by introducing new possible solutions to the population.

$$X_{jpar} = 2 * X_i \tag{8}$$

The X_{jpar} is the new organism want to invade the ecosystem. This is a battle of survival for organism X_j. If X_{jpar} is better than X_j, then X_j is replaced by X_{jpar} otherwise X_j hold on as shown in (9) for function minimization problems. The $\text{Obj}(X_j)$ and $\text{Obj}(X_{\text{jpar}})$ are the value of objective function for organism X_j and X_{jpar}, respectively.

$$X_{\text{jnew}} = \begin{cases} X_j & \text{if } Obj(X_j) < \text{Obj}(X_{\text{jpar}}) \\ X_{\text{jpar}} & \text{if } Obj(X_j) > \text{Obj}(X_{\text{jpar}}) \end{cases} \tag{9}$$

The proposed multi-agent-based symbiotic organism search

The structure of the basic SOS presented in Algorithm 2 involves the main program, which has access to organism status and memory and controls the organism's execution and the final solution. The implementation of basic SOS assumes that all organisms can interact directly and can access the optimal global solution in each iteration. In the proposed distributed SOS, each organism takes the property of the agent; therefore, it runs independently and autonomously. The proposed algorithm is purely distributed; agents only communicate through message passing. Upon receiving the states from neighbours, agents consider that information the ecosystem. Hence, at each iteration agent has no information about the global best; only it has information about the current states of neighbours, its state, and its local best. The best available state in the neighbourhood is used as the global best. In the distributed environment, the size of the agent's neighbourhood may be limited by the structure of the problem and the definition of neighbourhood. This fact may affect convergency and lead to the algorithm which is prone to local trapping. In order to improve the exploration and exploitation of the algorithm, modifications of SOS at the mutualism and parasitism phase have been made. The flowchart and pseudocode of the proposed multi-agent-based SOS are presented in Fig. 2 and Algorithm 3 of Appendix, respectively

Modification at the mutualism phase

At the mutualism phase, agents generate two new possible states using (5) and (6). It should be stated that in centralized SOS, organisms share a memory; that is, on the execution of organism i, two states can be updated, i.e. state X_{inew} and X_{jnew} according to (5) and (6). In the proposed distributed SOS, agents do not share a memory; they only exchange messages. Although two solutions are produced by agent i, an agent can only update its state. Comparing the centralized and proposed distributed SOS, in centralized SOS at the mutualism phase, it is possible to have two updates of the organisms in the population, while in a proposed distributed SOS, only one organism state can be updated. This aspect can make the convergence of the proposed algorithm inferior relative to the centralized SOS. In order to improve convergence at the mutualism phase, a simple approach that does not involve any additional function evaluation has been proposed. In the proposed MASOS, the best

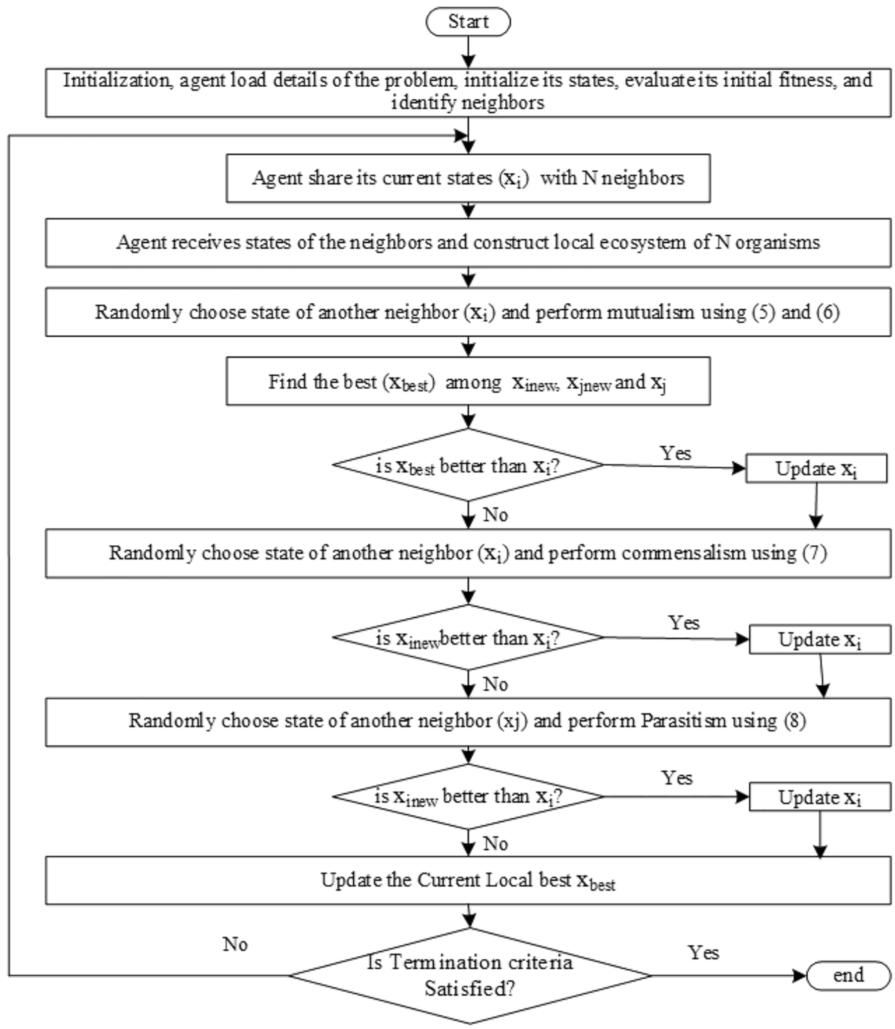

Fig. 2 Flowchart of a proposed multi-agent-based SOS

solution between, X_i, X_{inew} and X_{jnew} is preserved, unlike the centralized SOS, which takes the best between X_i and X_{inew} for updating the state of organism i.

Modification at parasitism phase

In the conventional SOS, the purpose of the parasitism phase is to increase exploration capability by trying to introduce new organisms into the ecosystem. This phase focuses much on improving the ecosystem and not necessarily improving agent i. In distributed SOS, the improvement in the population may have a small effect on the improvement in the state of the organism i, since, in distributed SOS, the focus of the agent is to update its own state. In order to improve the exploration capability of the algorithm, the agent X_i generates a parasite vector X_{jpar} as per (8). If X_{jpar} is better than X_i, the X_i update itself with new values X_{jpar} as given in (10).

$$X_{\text{inew}} = \begin{cases} X_{\text{jpar}} & \text{if } Obj(X_{\text{jpar}}) < \text{Obj}(X_i) \\ X_i & \text{Otherwise} \end{cases} \tag{10}$$

Results and discussion

The proposed algorithm was first implemented on benchmark functions for validation and then was applied for solving DG Coordination problems in the radial distribution network.

Validation of the proposed algorithm on benchmark functions

To validate the effectiveness of the proposed MASOS algorithm, an experimental study was performed using sets of benchmark functions. The proposed MASOS are compared with those offered by the original SOS and other algorithms through statistical analysis. Statistical analysis includes mean, standard deviation, and Wilcoxon ranks sum test.

Benchmark functions description

In this study, ten benchmark functions classified according to the characteristics, such as separable, non-separable, multimodal, and unimodal, obtained from [23] and listed in Table 1, are used. Functions f_1 to f_4 are two-dimensional problems and f_5 to f_{10} are thirty-dimensional problems. f_{10} is unimodal, separable function, f_2, f_3 and f_5 are unimodal, non-separable functions, f_1, f_4 and f_8 are multimodal, separable functions, f_6, f_7 and f_9 are multimodal, non-separable functions. It should be mentioned that difficulty of the problems differs depending on their type and dimension.

Parameter settings

The designed algorithm in this study is tested against other metaheuristic algorithms including original SOS [28], Particle Swarm Optimization (PSO) [29], Teaching Learning-Based Optimization (TLBO) [45] and Whale Optimization Algorithm (WOA) [31]. The authors implemented all the algorithms, and results were obtained from simulation

Table 1 Benchmark functions

Function name	Formula	Range	fmin
Booth(f_1)	$f_1(x,y) = (x+2y-7)^2 + (2x+y-5)^2$	[−10 10]	0
Easom(f_2)	$f_2(x,y) = -\cos(x_1)\cos(x_2)\exp(-(x-\pi)^2-(y-\pi)^2)$	[−100 100]	− 1
Matyas(f_3)	$f_3(x,y) = 0.26(x^2+y^2) - 0.48xy$	[−10 10]	0
*Bohachevsky*1(f_4)	$f_4(x,y) = x^2 + 2y^2 - 0.3\cos(3\pi x) - 0.4\cos(4\pi y) + 0.7$	[−100 100]	0
Ackley(f_6)	$f_{26}(x,y) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D} {x_i}^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{D}\cos(2\pi x_i)\right)$ $+20+e$	[−32 32]	0
Griewank(f_7)	$f_{25}(x,y) = \frac{1}{4000}\left(\sum_{i=1}^{D}(x_i-100)^2\right) - \left(\prod_{i=1}^{D}\cos(\frac{x_i-100}{\sqrt{i}})\right) + 1$	[−600 600]	0
Rastrigin(f_8)	$f_{24}(x,y) = \sum_{i=1}^{D}({x_1}^2 - 10\cos 2\pi x_i + 10)$	[−5.12 5.12]	0
Rosenbrock(f_9)	$f_{22}(x,y) = \sum_{i=1}^{D}100(x_{i+1} - {x_i}^2)^2(x_1-1)^2$	[−30 30]	0
Sumsquares(f_{10})	$f_18(x,y) = -\sum_{i=1}^{D} i{x_i}^2$	[−10 10]	0

experiments. For all algorithms size of the ecosystem/population was 30, and the maximum number of iterations per single run was 1000. In order to simplify the analysis, any value less than $1E^{-12}$ is considered as 0. All algorithms were implemented in the Java programming language, and MASOS was implemented in the Java Agent DEvelopment (JADE) multi-agent simulation framework. For MASOS, the structure of the neighbourhood has effects on the performance of the algorithm; in this work, all agents are considered as neighbours. All simulations were carried out using IntelliJ IDEA on 3.80GHz 4 Cores core i7 computer with 16GB RAM. The parameter settings for each algorithm are listed in Table 2.

Statistical analysis

Experiments were conducted to test the performance of proposed MASOS against SOS and other algorithms through statistical parameters such as mean, standard deviations (SD), and Wilcoxon ranks sum test. Mean and standard deviation results for all functions obtained after running the algorithms for 40 independent runs are presented in Table 3.

The results for Wilcoxon's rank-sum statistical test performed at 5% significant level are presented in Table 4. This significant level means that if the results show h=1 and p-values less than 0.05 points, it implies that the MASOS is better. If h=0 and p-values greater than 0.05 points, it implies that the MASOS is inferior. If h=0 and p-values are N/A, it implies that there is no significant difference between the two solution sets of compared algorithms.

It is observed from the results for two-dimensional functions $f_1 - f_4$ in Table 3 that all algorithms, including MASOS, were able to find a global minimum for all four functions except WOA, which could not find a global minimum for f_1. For f_5 the TLBO, SOS and MASOS were able to find a global minimum and outperformed PSO and WOA. For f_6 only SOS and MASOS were able to find the global minimum. For f_7 none of the algorithms found a global minimum, but WOA displays the best performance. WOA, SOS and MASOS were able to find a global solution for f_8. None of the algorithms found optimal global solutions for f_9, but the TLBO obtained the best mean value while WOA obtained the best standard deviation. As for f_{10} all algorithms were able to find a global solution except PSO.

The results for Wilcoxon's rank sum test for all functions $f_1 - f_{10}$ presented in Table 4 shows that when compared with PSO, the MASOS has achieved better results for six functions inferior for one function and for the rest functions, there was no significant difference. When compared with WOA, the MASOS has achieved better results for nine out of ten functions. When compared with TLBO, the MASOS has achieved better

Table 2 Parameter settings

PSO	WOA	TLBO	SOS	MASOS
$n = 30$	$n = 30$	$n = 30$	$n = 30$	$n = 30$
$w = 0.9 - 0.7$	$a = 0 - 2(lineear)$			
$\frac{x_{min}}{10} - \frac{x_{max}}{10}$				

Note: n = population/colony/ecosystem size; w = inertia weight; v = limit of velocity; a= distance control parameter

Table 3 Statistical results for benchmark functions

Function		PSO	WOA	TLBO	SOS	MASOS
f1	Mean	**0**	6.6250e-09	**0**	**0**	**0**
	SD	**0**	5.6615e-09	**0**	**0**	**0**
f2	Mean	**-1**	**-1**	**-1**	**-1**	**-1**
	SD	**0**	2.8278e-12	**0**	**0**	**0**
f3	Mean	**0**	**0**	**0**	**0**	**0**
	SD	**0**	**0**	**0**	**0**	**0**
f4	Mean	**0**	**0**	**0**	**0**	**0**
	SD	**0**	**0**	**0**	**0**	**0**
f5	Mean	26760.4943	1.2591	**0**	**0**	**0**
	SD	53853.2696	1.3177	**0**	**0**	**0**
f6	Mean	2.31158	1.2465e-08	0.16014	**0**	**0**
	SD	5.1792	1.0237e-08	0.5743	**0**	**0**
f7	Mean	28.2474	**0.02458**	0.4489	0.0286	0.03481
	SD	37.4861	**0.01995**	0.8317	0.0319	0.04125
f8	Mean	120.7342	**0**	14.6284	**0**	**0**
	SD	28.06463	**0**	5.4515	**0**	**0**
f9	Mean	14282.0493	25.1561	**8.7151**	17.2321	25.3948
	SD	32263.2366	**0.121**	1.6621	1.6754	0.2073
f10	Mean	660.0004	**0**	**0**	**0**	**0**
	SD	516.2987	**0**	**0**	**0**	**0**
Found best mean		4	6	7	8	8

The best results are highlighted in bold

Table 4 Results of the Wilcoxon's rank sum test for MASOS and other algorithms

	PSO		WOA		TLBO		SOS	
	p	***h***	***p***	***h***	***p***	***h***	***p***	***h***
f1	N/A	0	1.97E−16	1	N/A	0	N/A	0
f2	N/A	0	1.97E−16	1	N/A	0	N/A	0
f3	1.97E−16	1	1.97E−16	1	N/A	0	N/A	0
f4	N/A	0	N/A	0	N/A	0	N/A	0
f5	1.44E−14	1	1.44E−14	1	7.58E−15	1	7.58E−15	1
f6	2.13E−15	1	2.13E−15	1	1.43E−12	1	9.60E−08	1
f7	0.76915	0	6.24E−04	1	0.0334	1	1.81E−05	1
f8	1.99E−16	1	1.85E−09	1	1.97E−16	1	N/A	0
f9	2.71E−13	1	1.12E−08	1	1.44E−14	1	1.44E−14	1
f10	1.44E−14	1	1.41E−14	1	2.36E−13	1	1.44E−14	1
Count of better results		6		9		6		5

results for six functions and similar results for four functions. When compared with SOS, the MASOS has achieved better results for five functions and similar results for five functions.

Considering all functions, the results of the proposed MASOS have been at par with SOS for most functions. Considering the mean values of the algorithms, both SOS and MASOS were able to obtain the best results for eight functions, followed by TLBO, which obtained the best mean values for seven functions. The Wilcoxon rank sum test results show that the proposed MASOS has produced the same or better results than other considered algorithms for most functions. It can be stated that the proposed MASOS has been able to compete and outperform other proficient algorithms such as PSO, WOA and TLBO for most functions. The MASOS has shown better or similar results for most functions than its counterpart SOS algorithm. However, the MASOS has added the advantage that it has been designed for a distributed environment.

Application of MASOS for DG coordination in the electrical distribution network

Testing electrical distribution network

Tanzania Electric Supply Company (TANESCO) Limited is the only company that deals with the generation, transmission and distribution of electricity in Tanzania [46]. Due to the rapid expansion of the distribution network, the efficiency and reliable power supply are among challenges facing the Tanzania utility company. The improvements can be achieved through effective use of information and communication technologies (ICT). Therefore, this study proposes MASOS algorithm for coordinating DG in the Tanzanian electrical distribution network. The single-line diagram for a small power system section taken from the Tanzania secondary distribution network is shown in Fig. 3. The secondary distribution network comprises a three or a single-phase network with a neutral conductor. Single distribution transformers save loads in the secondary distribution networks; thus, a radial power flow analysis is used for identifying power system variables. More information about the line and load data of the network in Fig. 1 can be found in [47]. The network has 79 nodes numbered arbitrarily. The secondary distribution network is not static as it grows as new customers are connected to the network. According to authors in [47], from January 2015 to September 2019, Tanzania utility companies have a growth rate of 32% per year. This growth rate is significant for the distribution network as it is associated with changes in the topology and increases load demand, impacting system performances. Therefore, to ensure power system efficiency in such a dynamic system, DG can be used.

The advantages of DG inclusion can be reaped through their coordination. DG coordination here means changing DG outputs based on changing network parameters. In this study, load variations have been considered. The load data from 2012 to 2019 were

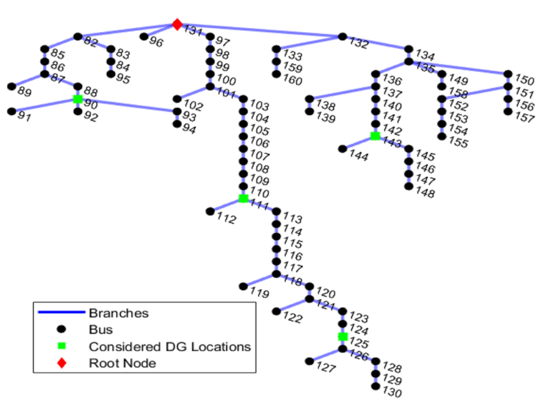

Fig. 3 Layout of considered section of Tanzanian power distribution network

obtained from TANESCO's Automatic Meter Reader (AMR). Data from meters were captured every 20 minutes and included voltage readings, current readings, and power readings. In this study, only current and voltage values were considered. The AMR data were converted from 20 minutes to hourly resolution for simplifying analysis. The sample Load Profile from the study area for three days is presented in Fig. 4.

In testing the efficacy of the proposed algorithm in coordinating DGs in the Tanzanian power system, the following assumptions and settings were considered: -

i. The DGs are controllable; that is, the power output can be changed
ii. Four DGs were considered and placed at buses 90, 111, 125 and 145, as shown in Fig. 3. Finding optimal DG places was not part of this study
iii. On each DG, there is a DG controller which can communicate with the neighbouring controller and run the MASOS algorithm
iv. The controller is responsible for changing the DG settings
v. Each hour is considered an individual control cycle, meaning that the settings of the DGs are maintained throughout the hour until the next hour when the load changes
vi. The available DG settings at any time are applied to the system, meaning there is no need to wait for the final converged value of the algorithm. This assumption ensures near real-time control of the DGs

Results for DGs coordination considering load variations

The proposed algorithm was applied to propose optimal DG settings in response to the changing load based on the stated assumptions. The system power loss and voltage deviation were considered using average hourly load data from 2012 to 2019. Experiments were conducted considering three cases. Firstly, hourly power loss and voltage deviations without any DG were calculated. Secondly, the DGs were placed, and the fixed DGs settings were maintained throughout all considered hours. Thirdly, the proposed

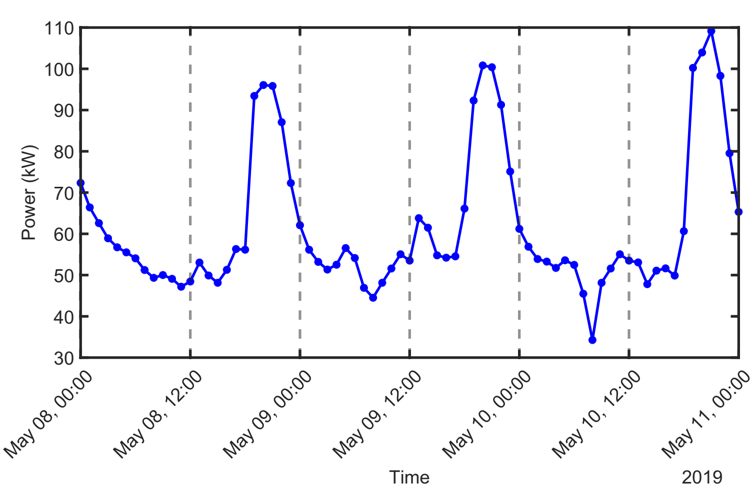

Fig. 4 Sample load data for three days

MASOS algorithm was applied to coordinate the operations of DGs by suggesting the optimal DG sizes for each loading condition accordingly. The power loss and voltage deviation results are presented in Figs. 5 and 6, respectively. The proposed DG settings for each hour are shown in Fig. 7.

It is observed in Fig. 5 that throughout the considered time, the power losses without DGs are higher than when DGs are involved. A similar observation is shown in Fig. 7, where the voltage deviation is large without DGs than with the involvement of DGs. Also, with a fixed size of DGs, though it can significantly improve power loss and voltage profile management, its muted response to changing load is a disadvantage. When the proposed

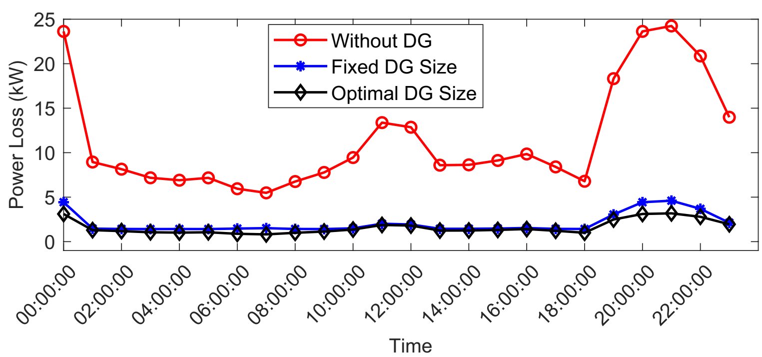

Fig. 5 The estimated hourly power losses for Tanzania power system

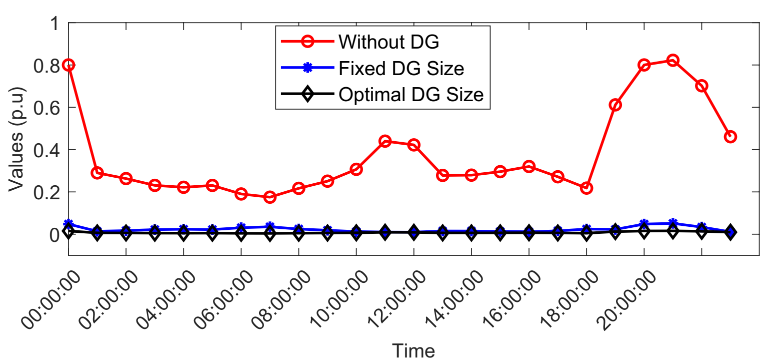

Fig. 6 The estimated hourly voltage deviation for Tanzanian power system

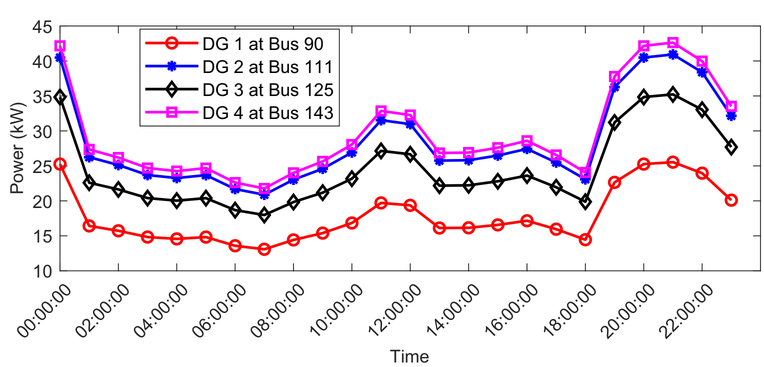

Fig. 7 The optimized hourly DG settings for study area power system

MASOS algorithm is employed, the power loss and voltage deviation are the minimum best. The total power loss per day without DGs is 276.1 kW, with fixed DG sizes is 49.5 kW, and with optimal DG sizes is 38.5 kW, which implies that the proposed DG coordination algorithm improves power system efficiency.

The proposed DG locations were bus 90, bus 111, bus 125 and bus 143. The proposed DG settings on each DG bus for each hour are presented in Fig. 7. For example, from Fig. 7, the DG settings at 8:00 at buses 90, 111, 125 and 143 are 14.4145 kW, 23.0252 kW, 19.8263 kW and 24.003734 kW, respectively.

Conclusion and future work

The designs of many metaheuristic algorithms are based on centralized programs for solving optimization problems which limit their use in distributed control. In this paper, a framework for integrating metaheuristic algorithms and MAS has been proposed. Based on the proposed framework, a new algorithm called MASOS derived from conventional SOS has been presented. The proposed MASOS was implemented in JADE, a distributed control framework for MAS. Standard mathematical benchmark functions of different types and different dimensions have been used to validate the proposed MASOS against other proficient algorithms such as PSO, WOA, TLBO and SOS. The results show that the proposed MASOS has been efficient in solving considered benchmark functions in a distributed manner. Subsequently, the proposed MASOS was applied for DGs coordination to enhance distribution network operations services using the electrical Distribution network segment from Tanzania's Electrical distribution network. Therefore, it can be concluded that the proposed MASOS is a good choice for solving engineering optimization problems in a distributed manner.

It should be mentioned that the proposed MASOS has been designed to handle changes in the power distribution systems. The future work to extend the proposed study could be to test the performance of the proposed algorithms considering other sources of uncertainty in power systems such as network reconfiguration, load shedding, and DG intermittency. In this study power loss have been considered main function, the proposed algorithm can also be tested for multi-objective functions. Regarding the proposed frameworks for MAS, the authors of this paper suggest that new MAS-integrated algorithms based on other metaheuristic algorithms apart from SOS can also be designed and tested. In MAS, agent neighbourhood structure plays an important role in determining the algorithm's performance. Therefore, studies to test the performance of algorithms for different types of neighbourhoods can contribute to improving the algorithm. Also, since the implementation of the proposed algorithm was based on MAS, which is near real-life simulation, the authors of this paper intend to implement the proposed MASOS algorithm in real-life application in a pilot site.

Appendix

See Algorithm 1,2 and 3

Algorithm 1 The Basic structure of Metaheuristic Algorithms

Initialization
while $iterations$ **do** //Outer Loop
  for each member **do** //Inner Loop
    Executes mathematical formulation of the algorithm
    Solution update rules
  end for// End of Inner Loop
  Check loop termination criteria (maximum number of iteration or tolerance limit)
end while// End of Outer Loop

Algorithm 2 The Basic structure of SOS

Initialization
while $it < maxite$ **do**
  Identify the best organism X_{best} in an ecosystem
  for $i = 1 : ecosystemsize$ **do**
    Mutualism
    Commensalism
    Parasitism
  end for
  Checking termination criterion
end while

Algorithm 3 Pseudocode of the Proposed MASOS Algorithm

Agent load details of the problem
Agent initialize its states, evaluate its initial fitness, and identify neighbours
while $it < maximum_iterations$ **do**
  // Ecosystem Formation
  Agent share current states x_i with N neighbours
  Agent Receives states of the neighbours and constructs a local ecosystem of N organisms
  Agent find the Current Local best x_{best} of the formulated population

//Mutualism
  Randomly choose the state of another neighbour x_j
  Perform mutualism using equations (5) and (6)
  Find the best (x_{Lbest}) state among x_{inew}, x_{jnew} and x_j
  if $x_{Lbest} < x_i$ **then**
    $x_i \leftarrow x_{Lbest}$
  end if

//Commensalism
  Randomly choose the state of another neighbour x_j
  Perform Commensalism using equations (7)
  if $x_{inew} < x_i$ **then**
    $x_i \leftarrow x_{inew}$
  end if

//Parasitism
  Randomly choose the state of another neighbour x_j
  Perform parasitism using equations (8) and (9)
  if $x_{jpar} < x_i$ **then**
    $x_i \leftarrow x_{jpar}$
  end if
  Update the Current Local best x_{best}
  Checking termination criterion
end while// End of Outer Loop

Abbreviations

ADMM	Alternating direction method of multipliers
AMR	Automatic meter reader
DG	Distributed generation
JADE	Java Agent DEvelopment Framework
MAS	Multi-agent system
MASOS	Multi-agent-based symbiotic organism search algorithm
PSO	Particle swarm optimization
SOS	Symbiotic organism search
TANESCO	Tanzania Electric Supply Company
TLBO	Teaching learning-based optimization
WOA	Whale optimization algorithm

Acknowledgements
Not applicable

Author contributions
SK proposed the idea and mainly involved in coding, designing the algorithm, and manuscript compilation. DM was involved in designing presentation of results and discussion, reviewing literature and editing the manuscript. Both authors read and approved the final manuscript.

Funding
Not applicable (no funding received for the research reported)

Availability of data and materials
All data generated or analysed during this study are included in this published article.

Declarations

Competing interests
The authors declare that they have no competing interest.

Received: 10 October 2022 Accepted: 10 January 2023
Published online: 23 January 2023

References

1. Shukla J, Panigrahi BK, Ray PK (2020) Stochastic reconfiguration of distribution system considering stability, correlated loads and renewable energy based DGs with varying penetration. Sustain Energy Grids Netw 23:100366
2. Kotsalos K, Miranda I, Silva N, Leite H (2019) A horizon optimization control framework for the coordinated operation of multiple distributed energy resources in low voltage distribution networks. Energies 12(6):1182
3. Panigrahi R, Mishra SK, Srivastava SC, Srivastava AK, Schulz NN (2020) Grid integration of small-scale photovoltaic systems in secondary distribution network-a review. IEEE Trans Ind Appl 56(3):3178–3195
4. Chen P-C, Salcedo R, Zhu Q, De Leon F, Czarkowski D, Jiang Z-P, Spitsa V, Zabar Z, Uosef RE (2012) Analysis of voltage profile problems due to the penetration of distributed generation in low-voltage secondary distribution networks. IEEE Trans Power Deliv 27(4):2020–2028
5. Bokhari A, Raza A, Diaz-Aguiló M, De Leon F, Czarkowski D, Uosef RE, Wang D (2015) Combined effect of CVR and DG penetration in the voltage profile of low-voltage secondary distribution networks. IEEE Trans Power Deliv 31(1):286–293
6. Kharrazi A, Sreeram V, Mishra Y (2020) Assessment techniques of the impact of grid-tied rooftop photovoltaic generation on the power quality of low voltage distribution network-a review. Renew Sustain Energy Rev 120:109643
7. Acharya D, Das DK (2022) An efficient optimizer for optimal overcurrent relay coordination in power distribution system. Expert Syst Appl 199:116858
8. Nadeem M, Imran K, Khattak A, Ulasyar A, Pal A, Zeb MZ, Khan AN, Padhee M (2020) Optimal placement, sizing and coordination of facts devices in transmission network using whale optimization algorithm. Energies 13(3):753
9. AkbaiZadeh M, Niknam T, Kavousi-Fard A (2021) Adaptive robust optimization for the energy management of the grid-connected energy hubs based on hybrid meta-heuristic algorithm. Energy 235:121171
10. Wang Y, John T, Xiong B (2019) A two-level coordinated voltage control scheme of electric vehicle chargers in low-voltage distribution networks. Electric Power Syst Res 168:218–227
11. Cheng Z, Li Z, Liang J, Si J, Dong L, Gao J (2020) Distributed coordination control strategy for multiple residential solar PV systems in distribution networks. Int J Electr Power Energy Syst 117:105660
12. Utkarsh K, Trivedi A, Srinivasan D, Reindl T (2016) A consensus-based distributed computational intelligence technique for real-time optimal control in smart distribution grids. IEEE Trans. Emerg Topics Comput Intell 1(1):51–60
13. Antoniadou-Plytaria KE, Kouveliotis-Lysikatos IN, Georgilakis PS, Hatziargyriou ND (2017) Distributed and decentralized voltage control of smart distribution networks: models, methods, and future research. IEEE Trans Smart Grid 8(6):2999–3008
14. Li Y, Tan C (2019) A survey of the consensus for multi-agent systems. Syst Sci Control Eng 7(1):468–482
15. Hou J, Xiang M, Ding Z (2019) Group information based nonlinear consensus for multi-agent systems. IEEE Access 7:26551–26557

16. Binetti G, Naso D, Turchiano B, Davoudi A, Lewis FL (2014) Consensus-based approach for the economic dispatch problem. IFAC Proc Vol 47(3):3140–3145
17. Ullah MH, Babaiahgari B, Alseyat A, Park J-D (2020) A computationally efficient consensus-based multiagent distributed ems for dc microgrids. IEEE Trans Ind Electron 68(6):5425–5435
18. Zhang B, Lam AY, Domínguez-García AD, Tse D (2014) An optimal and distributed method for voltage regulation in power distribution systems. IEEE Trans Power Syst 30(4):1714–1726
19. Maknouninejad A, Qu Z (2014) Realizing unified microgrid voltage profile and loss minimization: a cooperative distributed optimization and control approach. IEEE Trans Smart Grid 5(4):1621–1630
20. Šulc P, Backhaus S, Chertkov M (2014) Optimal distributed control of reactive power via the alternating direction method of multipliers. IEEE Trans Energy Convers 29(4):968–977
21. Zheng W, Wu W, Zhang B, Sun H, Liu Y (2015) A fully distributed reactive power optimization and control method for active distribution networks. IEEE Trans Smart Grid 7(2):1021–1033
22. Zhong W, Liu J, Xue M, Jiao L (2004) A multiagent genetic algorithm for global numerical optimization. IEEE Trans Syst Man Cybern Part B (Cybernetics) 34(2):1128–1141
23. Acharya DS, Mishra SK (2020) A multi-agent based symbiotic organisms search algorithm for tuning fractional order PID controller. Measurement 155:107559
24. Sarkar D, Kudkelwar S (2021) An over current relay coordination: a comparative analysis of metaheuristic and linear program approach. Int Trans Electr Energy Syst 31(12):13242
25. El-kordy M, El-fergany A, Gawad AFA (2021) Various metaheuristic-based algorithms for optimal relay coordination: review and prospective. Arch Comput Methods Eng 28(5):3621–3629
26. Qin C, Zheng J, Lai J (2007) A multiagent quantum evolutionary algorithm for global numerical optimization. In: International conference on life system modeling and simulation, Springer, pp 380–389
27. Zhao B, Guo C, Cao Y (2005) A multiagent-based particle swarm optimization approach for optimal reactive power dispatch. IEEE Trans Power Syst 20(2):1070–1078
28. Cheng M-Y, Prayogo D (2014) Symbiotic organisms search: a new metaheuristic optimization algorithm. Comput Struct 139:98–112
29. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95-international conference on neural networks, vol 4, IEEE, pp 1942–1948
30. Rao RV, Savsani VJ, Vakharia D (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43(3):303–315
31. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
32. Ezugwu AE, Adeleke OJ, Akinyelu AA, Viriri S (2020) A conceptual comparison of several metaheuristic algorithms on continuous optimisation problems. Neural Comput Appl 32(10):6207–6251
33. Gharehchopogh FS, Shayanfar H, Gholizadeh H (2020) A comprehensive survey on symbiotic organisms search algorithms. Artif Intell Rev 53(3):2265–2312
34. Karimyan P, Gharehpetian GB, Abedi M, Gavili A (2014) Long term scheduling for optimal allocation and sizing of dg unit considering load variations and dg type. Int J Electr Power Energy Syst 54:277–287
35. Saha S, Mukherjee V (2021) A novel multi-objective modified symbiotic organisms search algorithm for optimal allocation of distributed generation in radial distribution system. Neural Comput Appl 33(6):1751–1771
36. Das B, Mukherjee V, Das D (2016) Dg placement in radial distribution network by symbiotic organisms search algorithm for real power loss minimization. Appl Soft Comput 49:920–936
37. Lalitha MP, Babu PS, Adivesh B (2016) Optimal distributed generation and capacitor placement for loss minimization and voltage profile improvement using symbiotic organisms search algorithm. Int J Electr Eng 9(3):249–261
38. Sedighizadeh M, Esmaili M, Eisapour-Moarref A (2017) Hybrid symbiotic organisms search for optimal fuzzified joint reconfiguration and capacitor placement in electric distribution systems. INAE Lett 2(3):107–121
39. Quoc SN, Ngoc DV, et al (2020) Symbiotic organism search algorithm for power loss minimization in radial distribution systems by network reconfiguration and distributed generation placement. Mathematical Problems in Engineering. 2020
40. Boum AT, Ndjependa PR, Bisse JN et al (2017) Optimal reconfiguration of power distribution systems based on symbiotic organism search algorithm. J Power Energy Eng 5(11):1
41. Abd El-salam MF, Beshr E, Eteiba MB (2018) A new hybrid technique for minimizing power losses in a distribution system by optimal sizing and siting of distributed generators with network reconfiguration. Energies 11(12):3351
42. Quadri IA, Bhowmick S, Joshi D (2018) A comprehensive technique for optimal allocation of distributed energy resources in radial distribution systems. Appl Energy 211:1245–1260
43. Teng J-H (2003) A direct approach for distribution system load flow solutions. IEEE Trans Power Deliv 18(3):882–887
44. Mohmmadzadeh H, Gharehchopogh FS (2020) A new multi-agent approach for solving optimization problems with high-dimensional: case study in email spam detection
45. Rao RV, Savsani V, Balic J (2012) Teaching-learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems. Eng Optim 44(12):1447–1462
46. Joseph R, Mvungi N (2014) Concept of automation in management of electric power systems. Int J Electr Comput Eng 8(12):1856–1860
47. Kawambwa S, Mwifunyi R, Mnyanghwalo D, Hamisi N, Kalinga E, Mvungi N (2021) An improved backward/forward sweep power flow method based on network tree depth for radial distribution systems. J Electr Syst Inf Technol 8(1):1–18

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.