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Multi-agent and ant colony optimization for ship integrated power system network reconfiguration

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Abstract: Electric power is widely used as the main energy source of ship integrated power system (SIPS), which contains power network and electric power network. SIPS network reconfiguration is a non-linear large-scale problem. The reconfiguration solution influences the safety and stable operation of the power system. According to the operational characteristics of SIPS, a simplified model of power network and a mathematical model for network reconfiguration are established. Based on these models, a multi-agent and ant colony optimization (MAACO) is proposed to solve the problem of network reconfiguration. The simulations are carried out to demonstrate that the optimization method can reconstruct the integrated power system network accurately and efficiently.

Keywords: ship integrated power system (SIPS), multi-agent and ant colony optimization (MAACO), network reconfiguration, ring grid, fault recovery.

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1. Introduction

Ship integrated power system (SIPS) utilizes electric power propulsion. In this system, power network and electric power network are integrated for the equipment to run normally. The system is characterised by high efficiency and convenience. It can be seen that SIPS has gradually become a development trend [1]. SIPS can meet the power demand of different types of system, including medium voltage transmission, power conversion devices, zonal distribution systems, and power electric propulsion systems. With the continuous expansion of system scale, control mode and fault protection for SIPS are becoming more and more complex [2]. During the navigation, to ensure the normal and efficient operation of the power systems, the ability to reconfigure the network as soon as possible when the power system fails is necessary. Many researches and strategies of network reconfiguration are used in the terrestrial power system. However, they are less useful for SIPS, due to the difference between the two kinds of power systems. Some algorithms were proposed for the ship power system but not for integrated power system. SIPS is different from common ship power system in system scale, power capacity, network topology, and so on [3–9]. SIPS network reconfiguration is a large-scale, non-linear, and time-varying problem. It is difficult for existing algorithms to get the optimal solution. Thus the SIPS network reconfiguration method needs to be researched.

In this paper, a multi-agent and ant colony optimization (MAACO) is proposed. Ant colony optimization (ACO) is a probabilistic algorithm used to find the optimal path. Multi-agent system (MAS) can provide a good basis for building complex systems. Combined with the two techniques, a new method is presented for the SIPS network reconfiguration. After theoretical analysis and simulation, it can be shown that MAACO can reconfigure SIPS network very well.

2. Simplified network topology of SIPS and mathematical model for network reconfiguration

2.1 SIPS simplified network topology

SIPS generally consists of four power stations. Each power station has two generators. Jumper wires are used to connect the stations. The generator output is 4 000 V direct current (DC), which is converted to 700 V DC by converters, and then transmitted to distribution network in the DC area [10,11]. Inverters or choppers convert 700 V DC to 400 V AC or 230 V DC. There are three kinds of loads in SIPS, propulsion loads, important loads, and common loads. According to the loads' importance, they can be divided into three levels. Level 1 and Level 2 loads are usually equipped with normal transmission routes and standby transmission routes. When

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failures occur to SIPS, the system must change the state of the switches to isolate the failure loads, for Level 1 and Level 2 loads to get a maximum degree power restoration and to run normally. Besides, unimportant loads can be removed if necessary.

The electrical devices in SIPS (including feeders and jumper wires) are abstracted into branches. Meanwhile, the connection points in two devices (feeders and jumper wires) are abstracted into nodes. Once the node-branch topology model is established, branches and nodes can be numbered by using the priority search theory [12].

Fig. 1 shows the simplified network topology model. There are 96 branches, marked with "○", 33 nodes, marked with "□", eight generators G1−G8, four propulsion loads M1−M4, eight motor loads M5−M12, 24 static loads I1−I24, 28 power electronic devices P1−P28, four jumper wires L1−L4. Dot lines stand for the alternative transmission routes.

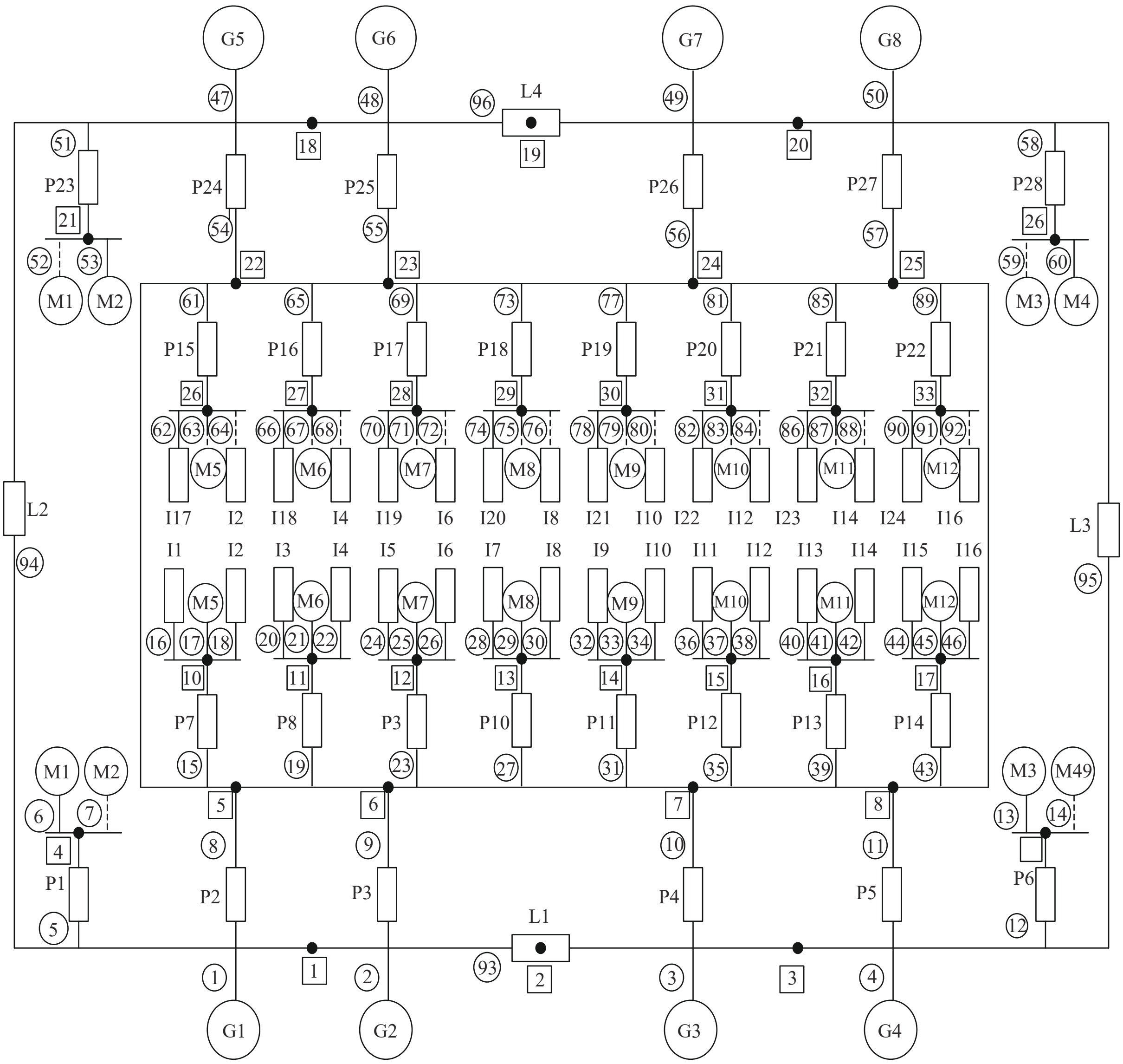


Fig. 1 SIPS simplified network topology

2.2 Mathematical model for network reconfiguration

After SIPS network reconfiguration, loads should be restored at a maximum extent. Loads ranked Level 1 and Level 2 must have the priority to be supplied. At the same time, the operation times of switches should be taken into account [13]. Based on the above requirements, the object function can be expressed as

$$\max F(x)=\sum_{i=1}^{n_1}\lambda_1 L_{g1i}+\sum_{i=1}^{n_2}\lambda_2 L_{g2i}+\sum_{i=1}^{n_3}\lambda_3 L_{g3i}-\eta S_x \quad (1)$$

where L_{g1i}, L_{g2i}, L_{g3i} represent three levels of loads, n_1, n_2, n_3 stand for the numbers of three level loads, λ_1, λ_2, λ_3 are the weight coefficients, S_x represents the switch operation time, and η stands for the punitive weight coefficient. Though choosing appropriate weight coefficients, the maximum number of loads restored and the minimum operation times of switches can be obtained. The values of the weighting coefficients can influence the results of simulations. In order to get the optimal values, many sets of weighting coefficients are selected for the simulations. Comparison of different simulation results from actual situations of SIPS shows that the best values of weighting coefficients are as follows: 1 for Level 1 loads, 0.1 for Level 2 loads, and 0.01 for Level 3 loads. By adopting this set of weight coefficients, simulations results are the closest to the real situations.

According to the real situation, the following constraint conditions should be considered in the network reconfiguration:

(i) Limitation of capacity: $P_i \leqslant \max P_i$

(ii) Limitation of voltage: $V_{\min} \leqslant V \leqslant V_{\max}$

(iii) Constraint on power flows: $\boldsymbol{UP}=\boldsymbol{D}$ where $\boldsymbol{U}$ refers to incidence matrix between branch and nodes, $\boldsymbol{P}$ represents feeder current vector, and $\boldsymbol{D}$ stands for load demand vector.

(iv) Transmission routes constraint: only one route connects with the load, the normal, or the alternative route.

(v) Priority constraint: loads are restored in turns according to the priority.

3. MAACO

3.1 Multi-agent for SIPS network reconfiguration

Because of the active behavioral capacity of agents, several agents can form a network of MAS even if they are loose coupled. Agents in MAS are separated from each other. They are self-government, and will not be affected by other agents. Through cerrain protocols, all agents can be linked together to solve one specific task or achieve the same goal. Therefore, MAS can be useful to solve a complex problem, which cannot be achieved by a single agent [14–18]. MAS adopts regional control. On the same regional feeder, the group of non-switch devices controlled by switches is considered as one agent.

Based on the above viewpoints, several feeder units can be found, and each one can be abstract as a regional agent. A multi-agent model of SIPS network is proposed, as shown in Fig. 2.

Agents are intelligent and autonomous. Not only can they make judgments and decisions, but also communicate with agents nearby, so as to maintain the safety and stable operation of SIPS [19–21].

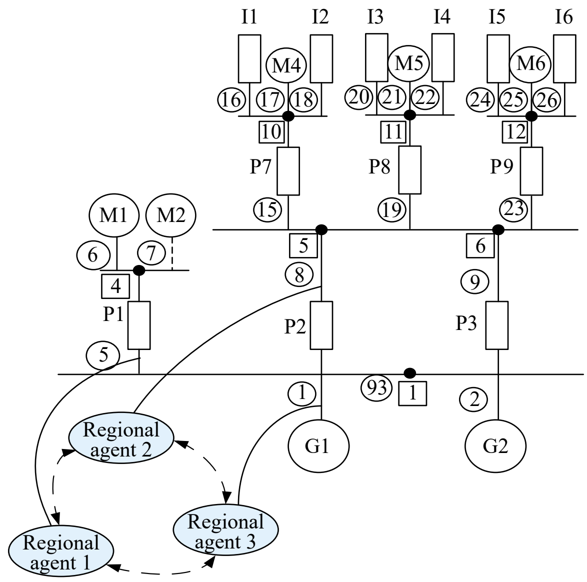


Fig. 2 Multi-agent model of SIPS network

3.2 ACO

Traditional ACO is probability-based, which is used to find the optimal path of the graph [22,23]. When ants move from the initial point i to the end point j, the probability of ants choosing the path (i, j) is determined by pheromone of the edge (i, j) and local heuristic information. To solve subset problems, we can set pheromone on vertexes. Whether vertexes join in the subset or not is determined by pheromone and local heuristic information on them [24–27].

(i) The strategy of probability selection. When time is t, the partial solution to ant k is supposed as $\tilde{S}_k(t)=\langle i_1, i_2, \cdots, i_j \rangle$. The probability of ant k choosing vertex i_p to join in $\tilde{S}_k(t)$ at time t is set as $p^k_{i_p}(t)$, which can be expressed as

$$P^k_{i_p}(t)=\begin{cases} \dfrac{[\tau_{i_p}(t)]^{\alpha}[\eta_{i_p}(t)]^{\beta}}{\sum\limits_{i_s \in \text{allowed}_k(t)} [\tau_{i_s}(t)]^{\alpha}[\eta_{i_s}(t)]^{\beta}}, & i_p \in \text{allowed}_k(t) \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $\tau_{i_p}>(t)$ is pheromone of vertex i at time t, $\eta_{i_p}(t)$ is the local heuristic information on vertex i at time t. In this paper, local heuristic information is the set to the importance of the load in network reconfiguration. α, β are parameters for the relative importance of pheromone and heuristic information. The collection of vertexes allowed$_k(t)$ includes all vertexes which ant k can choose when time is t.

A pseudo-random proportion principle should be adopted to avoid partial stagnation. With prior knowledge and to explore new paths, the strategy of probability selection is modified as follows:

$$P^k_{i_p}(t)=\max\{[\tau_{i_p}(t)]^{\alpha}[\eta_{i_p}(t)]^{\beta}\}, \quad q \leqslant q_0 \tag{3}$$

where q_0 $(q_0 \leqslant 1)$ is a parameter set in advance for new path exploration. A random decimal named q ($q \leqslant 1$) is used to judge whether to choose prior knowledge or possibility selection first. In other words, if $q > q_0$, we explore new paths according to possibility selection with (2); otherwise choose the vertex with the largest pheromone and heuristic information.

(ii) The strategy of global pheromone updates. To solve subset problems, pheromones used in the ACO needs to be set on vertexes, therefore pheromone variables need dimensionality reduction to one-dimension, which is defined as follows:

$$\tau_i(t+1) = (1-\rho_1)\tau_i(t) + \rho_1 \Delta\tau_i(t, t+1) \tag{4}$$

where ρ_1 is the global pheromone's volatile coefficient. Q is a constant, determined by the objective function $F(x)$, which is used to adjust weights of the optimal pheromone.

$$\Delta\tau_i(t, t+1) = \begin{cases} QF(x), & \text{when vertex } i \text{ is the best} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

(iii) The strategy of local pheromone updates. Ants can update the pheromone during the process of searching a path, which is defined as

$$\tau_i(t+1) = (1-\rho_2)\tau_i(t) + \rho_2 \Delta\tau \tag{6}$$

where $0<\rho_2<1$ represents a local update parameter, and $\Delta\tau$ stands for the increment of pheromone when ants pass through vertexes during the process. Usually $\Delta\tau$ is a constant.

(iv) The restriction strategy of pheromone. The pheromone on the path is limited in the interval $[\tau_{\min}, \tau_{\max}]$. The pheromone on the path is limited in a reasonable range, which can reduce the probability of stagnation. The upper and lower limits of pheromone can be defined as

$$\begin{cases} \tau_{\max} = \dfrac{1}{(1-\rho_1)} \dfrac{1}{F_{\text{best}}} \\ \tau_{\min} = \dfrac{\tau_{\max}(1-\sqrt[n]{0.05})}{(\text{avg}-1)\sqrt[n]{0.05}} \end{cases} \tag{7}$$

where F_{best} represents the global optimal solution and n represents the number of decisions an ant needs to make an iteration. The initial value of pheromone is set to be $\tau_{\max}$.

3.3 Strategy of *K*-nearest neighbor

In traditional ACO, the optimal solution to the combinatorial optimization problem can be obtained. With the change of the local update parameter, the space near the known optimal solution can be effectively searched. The load power and its weight coefficient are used as the basis of the K-nearest neighbor strategy selection. The strategy of the K-nearest neighbor has the ability of neighborhood search and ensures the search of a better solution.

With the use of the K-nearest neighbor strategy, the convergence speed of the traditional ACO can be improved by reducing the scope of search space reasonably [28,29]. Considering the features of SIPS network reconfiguration, the specific strategy can be summarized as follows:

(i) Establish K order-tables of restored loads after initializing ant colony. Each restored load is ranked in K order-tables according to $\lambda_i L_{gij}$, in which L_{gij} refers to the load power and λ_i refers to the weight coefficient.

(ii) Restore the highest ranking load (load with the maximum value of $\lambda_i L_{gij}$) in order-tables and adjusting the remaining capacity of SIPS.

(iii) If the system capacity is sufficient, remaining loads can be restored according to the rank in tables. The principle is to give priority to recovering loads with higher levels.

(iv) The value of K: we need to make a variety of attempts to decide the value of K. The value of K is usually taken directly from 3 to 10, or is equal to the square root of the training data. In order to accelerate the speed and improve the efficiency, the value of K needs to be small in the initial stage of ACO. On the contrary, for the purpose of recover loads as much as possible in the final stage, the value of K needs to be bigger.

3.4 MAACO

On the basis of ACO and multi-agents with the characteristics, such as autonomous learning, competition, and collaboration, the algorithm named MAACO is proposed. In MAACO, each agent has the ability of self-learning and can compete and cooperate with its neighbors. Based on ACO, information can be shared between current agent and global optimal agent. The agent's action strategy is modified according to its own experience. When failures occur, the neighboring agents can be selected first for small-scale network reconfiguration based on the characteristics of the agents. When the small-scale network reconfiguration is unable to complete failure recovery, the global network reconfiguration is carried out. MAACO can converge to the global optimal solution faster and more accurately. Regional feeder agents are defined in Fig. 2. In MACCO, agents can get the evolutional mechanism of ACO by autonomous learning and data exchanging with agents nearby. The ant colony is updated according to pre-set rules. In this way, the colony can get the optimal path more quickly and accurately [30–32].

In MAACO, a regional agent can be regarded as an ant in the ant colony. Thus we can determine the topology of the ant colony of SIPS network reconfiguration. Solutions to SIPS network reconfiguration can be obtained by agents' autonomous update and cooperate with agents nearby. The multi-agent can get the optimal value of objective function in ACO. Fig. 3 shows the flow chart of network reconfiguration based on MAACO.

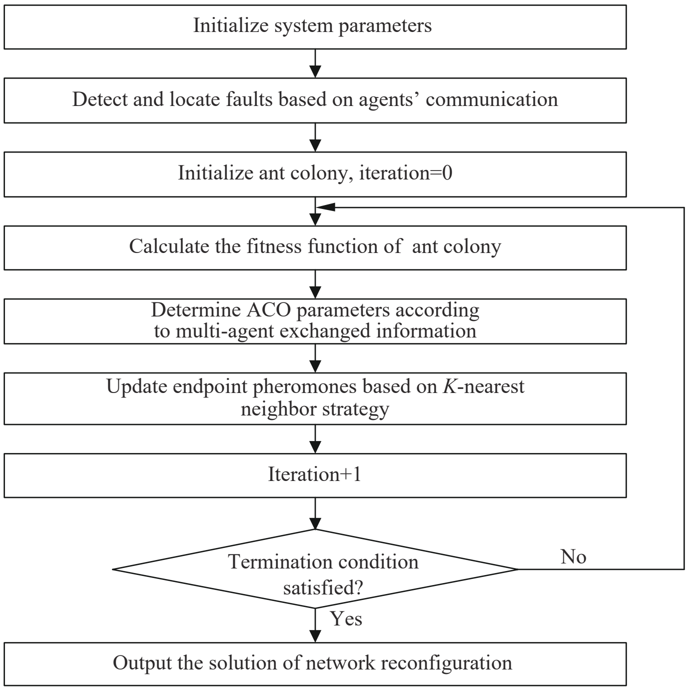


Fig. 3 Flow chart of network reconfiguration based on MAACO

4. Simulation

The network model of SIPS shown in Fig. 1 is used to carry out network reconfiguration simulations to verify the effectiveness of the proposed MAACO. Based on the actual fault situation of SIPS, two examples are proposed in the follwing subsections.

All the simulations are implemented by Matlab R2018b platform. The simulation computer is equipped with i5-5350H CPU, 8 GB RAM and Windows 7 operating system.

The simulation parameters are derived from the real SIPS. All the parameters of the SIPS devices are normalized, which can be seen in Table 1.

Table 1 Parameters of SIPS devices

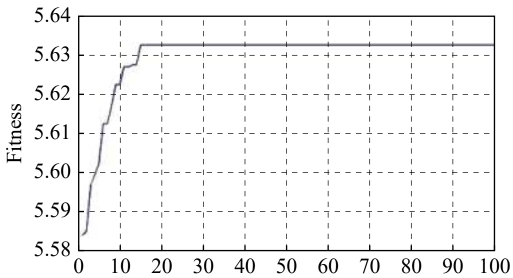
No.	Device	Power/kW	Level	No.	Device	Power/kW	Level	No.	Device	Power/kW	Level	No.	Device	Power/kW	Level
1	G1	21	0	25	M7	1.270 5	2	49	G7	3.75	0	73	P18	0.005	0
2	G2	3.75	0	26	I6	0.769 2	2	50	G8	21	0	74	I20	0.05	3
3	G3	3.75	0	27	P10	0.005	0	51	P23	0.005	0	75	M8	1.270 5	2
4	G4	21	0	28	I7	0.05	3	52	M1	20	1	76	I8	3.0	2
5	P1	0.005	0	29	M8	1.270 5	2	53	M2	20	1	77	P19	0.005	0
6	M1	20	1	30	I8	3.0	2	54	P24	0.005	0	78	I21	0.05	3
7	M2	20	1	31	P11	0.005	0	55	P25	0.005	0	79	M9	1.270 5	2
8	P2	0.005	0	32	I9	0.05	3	56	P26	0.005	0	80	I10	1.493 7	2
9	P3	0.005	0	33	M9	1.270 5	2	57	P27	0.005	0	81	P20	0.005	0
10	P4	0.005	0	34	I10	1.493 7	2	58	P28	0.005	0	82	I22	0.005	3
11	P5	0.005	0	35	P12	0.005	0	59	M3	20	1	83	M10	0.729 5	2
12	P6	0.005	0	36	I11	0.005	3	60	M4	20	1	84	I12	1.270 5	2
13	M3	20	1	37	M10	0.729 5	2	61	P15	0.005	0	85	P21	0.005	0
14	M4	20	1	38	I12	1.270 5	2	62	I17	0.05	3	86	I23	0.05	3
15	P7	0.005	0	39	P13	0.005	0	63	M5	1.270 5	2	87	M11	1.270 5	2
16	I1	0.05	3	40	I13	0.05	3	64	I2	1.102 4	2	88	I14	1.392	2
17	M5	1.270 5	2	41	M11	1.270 5	2	65	P15	0.005	0	89	P22	0.005	0
18	I2	1.102 4	2	42	I14	1.392	2	66	I18	0.05	3	90	I24	0.005	3
19	P10	0.005	0	43	P14	0.005	0	67	M6	0.897 6	2	91	M12	0.769 2	2
20	I3	0.05	3	44	I15	0.005	3	68	I4	1.493 7	2	92	I16	1.230 8	2
21	M6	0.897 6	2	45	M12	0.769 2	2	69	P17	0.005	0	93	L1	0.005	0
22	I4	1.493 7	2	46	I16	1.230 8	2	70	I19	0.05	3	94	L2	0.005	0
23	P9	0.005	0	47	G5	21	0	71	M7	1.270 5	2	95	L3	0.005	0
24	I5	0.05	3	48	G6	3.75	0	72	I6	0.769 2	2	96	L4	0.005	0

In the simulations, the ant colony represents the different states of branches of SIPS, with “1” for circuit closed and “0” for circuit open [33].

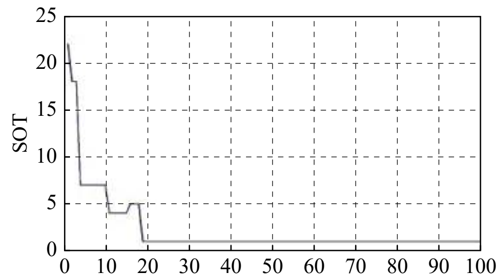
4.1 Example 1

Supposing that Agent 17 fails, the simulation results of network reconfiguration using MAACO are (i) Agent 63: the initial state is 0, and the final state is 1 and (ii) the fitness value is 5.632 85 and the switch operation times (SOT) is 1.

Fig. 4 shows the variation tendency of the fitness value and SOT.



(a) Trend of fitness value



(b) Trend of SOT

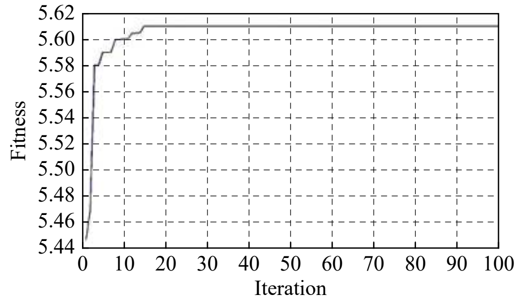
Fig. 4 Simulation results in Example 1

4.2 Example 2

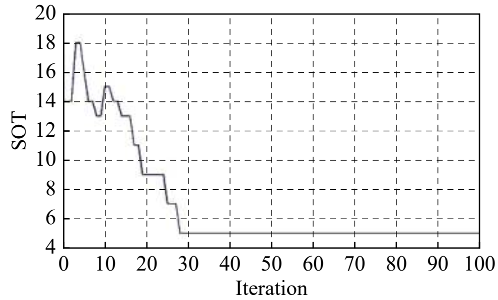
Suppose that Agents 3, 31, 93, and 95 fail, and the simulation results of network reconfiguration using MAACO are

(i) Agent 79: the initial state is 0, and the final state is 1;
(ii) Agent 80: the initial state is 0, and the final state is 1;
(iii) Agent 84: the initial state is 0, and the final state is 1;
(iv) the fitness value is 5.610 25 and SOT is 3.

Fig. 5 shows the variation tendency of fitness values and SOT.



(a) Trend of fitness value



(b) Trend of SOT

Fig. 5 Simulation results in Example 2

In the beginning of reconfiguration, the fault agents communicate with agents nearby. The neighbor agents estimate self-capacity firstly. If all constraint conditions given above are satisfied, the fault agents can be power supplied by alternative routes. After simulation, it can be found that in the 15th iteration, MAACO gets the best fitness value 5.610 25. However, the minimum number of SOT is three which can only be achieved until the 28th iteration. Therefore, we can get the best reconfiguration solution after 28 times of iterations.

5. Comparison

5.1 Comparison between MAACO and traditional ACO

Simulations are carried out by the use of traditional ACO and MAACO. Simulation results are recorded in Table 2 and Table 3.

It can be seen that the MAS accelerates the convergence speed of ACO in Example 1. MAACO changes the network topology in the minimum scope to reconfigure in Example 2 based on communication between different agents.

Table 2 Comparison between traditional ACO and MAACO in Example 1

Algorithm	Fitness value			SOT			Best iteration
	Maximum	Minimum	Average	Maximum	Minimum	Average	
Traditional ACO	5.632 55	5.508 03	5.586 26	26	1	5.8	29
MAACO	5.632 85	5.508 32	5.623 04	23	1	3.9	19

Table 3 Comparison between traditional ACO and MAACO in Example 2

Algorithm	Fitness value			SOT			Best iteration
	Maximum	Minimum	Average	Maximum	Minimum	Average	
Traditional ACO	5.602 15	5.506 82	5.545 87	25	6	8.8	37
MAACO	5.610 25	5.554 64	5.591 93	19	3	5.4	28

The numbers of best iteration and SOT in the simulation results are reduced by MAACO. The decreased number of the best iteration means the reduction of the algorithm's calculated quantities. The convergence speed is accelerated. Real-time performance of SIPS network reconfiguration with MAACO is better. The reduction of SOT means fewer changes in topology of SIPS. The system can be less influenced during network reconfiguration.

Therefore, MAACO can get a better solution than traditional ACO in SIPS network reconfiguration.

5.2 Comparison between MAACO and other algorithms

Simulations have been done by the use of the genetic algorithm (GA), particle swarm optimization (PSO), and MAACO. In order to ensure the validity of the data, each algorithm is simulated 50 times. The average value of each result is recorded in Table 4 and Table 5 as follows.

Table 4 Comparison between MAACO and other algorithms in Example 1

Algorithm	Average fitness value	Average SOT	Best iteration
GA	5.587 36	4.5	32
PSO	5.608 79	4.2	28
MAACO	5.623 04	3.9	19

Table 5 Comparison between MAACO and other algorithms in Example 2

Algorithm	Average fitness value	Average SOT	Best iteration
GA	5.584 39	7.9	39
PSO	5.620 54	6.8	35
MAACO	5.591 93	5.4	28

Through the comparison of data, it can be found that the number of fitness value between GA, PSO, and MAACO are basically same. The problem of SIPS network reconfiguration is solved by any algorithm. However, the number of SOT and of the best iteration are improved by the use of MAACO for Examples 1 and 2.

By the comparing with other intelligent algorithms, MAACO can not only accelerate the convergence speed, but also reduce the number of changes in topology of SIPS. The effectiveness and advanced nature of MAACO can be explained.

6. Conclusions

In this paper, the SIPS simplified network model and the mathematical model for network reconfiguration are set up. MAS, ACO, and the strategy of K-nearest neighbor are analyzed theoretically. Multi-agent, ACO, and MAACO are combined. Simulation results and data comparisons show that MAACO can improve the characteristic of real-time by accelerating the convergence speed of the algorithm. It can also reduce the switch operation times for less influence on the whole power system. MAACO is very suitable for SIPS network reconfiguration, which can effectively improve the sustainability of SIPS.

References

[1] JIN Z M, SAVAGHEBI M, VASQUEZ J C, et al. Maritime DC microgrids: a combination of microgrid technologies and maritime onboard power system for future ships. Proc. of the 8th IEEE International Power Electronics and Motion Control Conference, 2016: 179–184.

[2] ZHANG S X, CHENG H Z, WANG D, et al. Distributed generation planning in active distribution network considering demand side management and network reconfiguration. Applied Energy, 2018, 228: 1921–1936.

[3] HOSSAIN M R, GINN H L. Real-time distributed coordination of power electronic converters in a DC shipboard distribution system. IEEE Trans. on Energy Conversion, 2017, 32(2): 770–778.

[4] ALAFNAN H, ZHANG M, YUAN W, et al. Stability improvement of DC power systems in an all-electric ship using hybrid SMES/battery. IEEE Trans. on Applied Superconductivity, 2018, 28(3): 5700306.

[5] LI J, ZHANG Z P, LI B Y. Sensor fault detection and system reconfiguration for DC-DC boost converter. Sensors, 2018, 18(5): 1375.

[6] MORADI R, ALIKHANI A, JEGARKANDI M F. Comparing the performance of reference trajectory management and controller reconfiguration in attitude fault tolerant control. Proc. of the MATEC Web of Conferences, 2018, 151: 04008.

[7] GARAU M, GHIANI E, CELLI G, et al. Co-simulation of smart distribution network fault management and reconfiguration with LTE communication. Energies , 2018, 11(6): 1332.

[8] FENG X Y, BUTLER-PURRY K L, ZOURNTOS T. Real-time electric load management for DC zonal all-electric ship power systems. Electric Power Systems Research, 2018, 154: 503–514.

[9] SUN R J, LIU Y T, ZHU H N, et al. A network reconfiguration approach for power system restoration based on preference-based multi-objective optimization. Applied Soft Com-

puting, 2019, 83: 105656.
[10] SULTANA N, RUFENACHT M, SKJELLUM A, et al. Failure recovery for bulk synchronous applications with MPI stages. Parallel Computing, 2019, 84: 1–14.
[11] LI W B, LI Q, GAO J J, et al. Research of non-contact compensation AC voltage regulator based on fuzzy strategy. Journal of Physics: Conference Series, 2020, 1626(1): 012070.
[12] WANG Z, XIA L, WANG Y J. Application of multi-agent and genetic algorithm in network reconfiguration of ship power system. Electronics & Electrical Engineering, 2012, 18(9): 7–10.
[13] FOERSTER J, FARQUHAR G, AFOURAS T, et al. Counterfactual multi-agent policy gradients. Proc. of the AAAI Conference on Artificial Intelligence, arXiv preprint arXiv:1765.0892601, 2018
[14] ZHOU T, LIU Q L, WANG D, et al. Distributed non-fragile containment control of nonlinear multi-agent systems with time-varying delays. International Journal of Systems Science, 2020: 1–16.
[15] ALI M S, AGALYA R, ORMAN Z, et al. Leader-following consensus of non-linear multi-agent systems with interval time-varying delay via impulsive control. Neural Processing Letters, 2021, 53(1): 69–83.
[16] HOUSSEYNI W, MOSBAHI O, KHALGUI M, et al. Multiagent architecture for distributed adaptive scheduling of reconfigurable real-time tasks with energy harvesting constraints. IEEE Access, 2017, 6: 2068–2084.
[17] LOWE R, WU Y I, TAMAR A, et al. Multi-agent actor-critic for mixed cooperative-competitive environments. Advances in Neural Information Processing Systems, 2017, 30(1): 6379–6390.
[18] PANASETSKY D, SIDOROY D, LI Y, et al. Centralized emergency control for multi-terminal VSC-based shipboard power systems. International Journal of Electrical Power & Energy Systems, 2019, 104: 205–214.
[19] LI C J, LIU G P. Data-driven consensus for non-linear networked multi-agent systems with switching topology and time-varying delays. IET Control Theory & Applications, 2018, 12(12): 1773–1779.
[20] LI C J, LIU G P. Consensus for heterogeneous networked multi-agent systems with switching topology and time-varying delays. Journal of the Franklin Institute, 2018, 355(10): 4198–4217.
[21] CHNITER H, LI Y, KHALGUI M, et al. Multi-agent adaptive architecture for flexible distributed real-time systems. IEEE Access, 2018, 6: 23152–23171.
[22] BONABEAU E, DORIGO M, MARCO D, et al. Swarm intelligence: from natural to artificial systems. Oxford: Oxford University Press, 1999.
[23] DORIGO M, GAMBARDELLA L M. Ant colony system: a cooperative learning approach to the traveling salesman problem. IEEE Trans. on Evolutionary Computation, 1997, 1(1): 53–66.
[24] DI CARO G, DORIGO M, GAMBARDELLA L M. Ant algorithms for discrete optimization. Artificial Life, 1999, 5(2): 137–172.
[25] ARIYASINGHA I, FERNANDO T G I. Performance analysis of the multi-objective ant colony optimization algorithms for the traveling salesman problem. Swarm & Evolutionary Computation, 2015, 23: 11–26.
[26] KUZNETSOV A V, SELVESIUK N I, PLATOSHIN G A, et al. Application of cellular automatons and ant algorithms in avionics. Journal of Physics Conference Series, 2018, 973(1): 012062.
[27] LIU H D, SUN Y, ZHANG L Y. Information reconstruction strategy for a ship power distribution system. Proc. of the Data Processing Techniques and Applications for Cyber-Physical Systems, 2020: 479–487.
[28] PAPERNOT N, MCDANIEL P. Deep k-nearest neighbors: towards confident, interpretable and robust deep learning. arXiv preprint arXiv: 1803.04765, 2018.
[29] GOU J P, MA H X, OU W H, et al. A generalized mean distance-based k-nearest neighbor classifier. Expert Systems with Applications, 2019, 115: 356–372.
[30] YANG J. Research on optimized reconfiguration of distributed distribution network based on ant colony optimization algorithm. Proc. of the International Conference on Computer Engineering and Application, 2020: 20–23.
[31] DORIGO M, BIRATTARI M, STUTZLE T. Ant colony optimization. IEEE Computational Intelligence Magazine, 2006, 1(4): 28–39.
[32] SHEN X L, SANG J S, SUN Y B, et al. Application of improved ant colony algorithm in distribution network patrol route planning. Proc. of the 7th IEEE International Conference on Software Engineering and Service Science, 2016: 560–563.
[33] TIRKOLAEE E B, ALINAGHIAN M, HOSSEINABADI A, et al. An improved ant colony optimization for the multi-trip capacitated arc routing problem. Computers & Electrical Engineering, 2019, 77: 457–470.

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