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Self-healing reconfiguration scheme for distribution network with distributed generations based on multi-agent systems

Sun Hongbin[1] · **Zhang Yong**[2] · **Hu Bin**[3]

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Abstract More and more distributed generations are connected in the distribution network. Intermittent output and different locations have a significant impact to the distribution network voltage, current, power flow, the traditional forward and backward substitution is unable to solve PV-type node and meshed network, the distributed generations increase the number of network constraints and increase the difficulty of searching the optimal solution. To solve the problem of classic self-healing method failure, based on the multi-agent system, a novel self-healing reconfiguration scheme is proposed for distribution network with distributed generations in this study. Multiple objectives are considered for minimum distributed generation output loss, minimum power loss, load balancing among the feeders and branch current constraint violation, improved forward-backward weep method is used to get power flow solution for different node types of distributed generations, a self-adaptive differential evolution algorithm with improved strategies is proposed to solve problem. The performance of proposed algorithm is analyzed for several case studies on IEEE 33-bus system. The simulation results show that the approach can improve the self-healing reconfiguration performance and adapt to the changes of dynamic conditions.

✉ Sun Hongbin
win_shb@163.com

Zhang Yong
yongz@jlu.edu.cn

Hu Bin
BinH@Cse.Tamu.edu

1 School of Electrical Engineering, Changchun Institute of Technology, Changchun, China

2 College of Computer Sciences and Technology, Jilin University, Changchun, China

3 Department of Electrical Engineering, Texas A&M University, College Station, USA

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1 Introduction

With the development of smart grid technology, the basic protection and automation schemes have changed to distributed and communicative architectures, which system operation applications are more advanced to coordinate distributed intelligence on substations and feeders by ensuring reliability, efficiency and security. Those operational advances originate in the self-healing applications that minimize service disruption through the employment of modern technologies that can acquire data, execute decision-support algorithms, avert or limit interruptions, control the power flow dynamically and restore distribution network service quickly.

More and more distributed generations (DGs) are connected in distribution network. DGs may have an effect on steady operation and power quality. The connection of distributed generation sources has great influence on several aspects of the distribution network, especially in system reconfiguration [1]. Distributed generation connection leads to the emergence of new nodes in distributed network. Thus, the calculation method of the conventional back/forward sweep power flow is failed. In general, DGs do not participate in the frequency regulation of the system, thus its active power output is specified. However, the mode of reactive power and voltage depends on the circumstances. The main distribution network self-healing problem is to find a radial operating structure that minimum power loss and nodes voltage deviation based on operating constraints, the method of self-healing reconfiguration have to be modified with DGs [2].

To complete self-healing reconfiguration, the key lies in using the technique of distributed artificial intelligence to combine protection schemes with automatic restoration algorithms, multi-agent represents the best way to design it. The multi-agent methods guarantee an intelligent global response to self-healing of distribution network based on interactions among agents. Self-healing agent should anticipate and respond to system disturbances through the performance of self-assessment to detect, analyze and take corrective actions against dangerous events. The decision maker acquires data related to the system state and determines a feasible set of control actions proactively in response to fundamental questions. The agent architecture can be built to manage different aspects of information processing, which sends the control messages to other system agents [3–5]. Thus, the self-healing coordinator agent ensures suitable control decisions to maximize system efficiency and minimize the negative impacts of faults.

Based on the above analysis, this study examines a core problem in the design of self-healing reconfiguration scheme. Then, based on the multi-agent system, multiple objectives take into account the minimum power loss, the minimum distributed power output loss, branching current constraint violation and load balancing among the feeders.

In this paper, improved forward-backward weep method is used to calculate the power flow of different types of distributed power generation, multiple objectives are considered for minimum distributed generation output loss, minimum power loss and branch current constraint violation, and a modified self-adaptive differential evolution algorithm with improved strategies is proposed to solve optimization problem.

2 State of the art

Self-healing reconfiguration for distribution network is a mixed-integer, non-linear optimization problem. Distribution network system reconfiguration for loss reduction was first proposed by Merlin and Back [6]. The network switches are closed then opened successively, a branch-and-bound-type optimization technique is used to get the minimum loss configuration based on the optimum flow pattern [7]. The radial constraint and discrete nature prevent the classical techniques, the original method have to be modified for self-healing reconfiguration.

Artificial intelligence is an effective way to reconfiguration. An adaptive particle swarm optimization in conjunction has been used for distribution network [8]. The improved genetic optimization algorithm is used to determine the power loss reduction and reliability improvement indicators of the switch operation scheme [9]. A non-dominated sorting genetic algorithm (FNSGA) is designed to solve the DSR problem. The objectives are to minimize power losses and the voltage profile and load balancing index with minimum switching operations [10]. The method of active power distribution systems is proposed based on various criteria in a flexible and robust approach [11]. Those methods get good effect, but it does not consider the impact of DGs on the reconstruction. The distribution network has changed from a simple radiation network to a multi-power network, with the randomness and intermittent of wind power and photovoltaic power, the method of distribution network reconfiguration based on mathematical programming, branch switching method and artificial intelligence algorithm cannot completely solve the problem, the method of power flow calculation needs to be improved with DGs.

A particle swarm optimization way of allocation DG of low voltage profile is proposed [12]. Ant colony optimization and harmony search algorithm are combined for the reconfiguration problem [13]. The fuzzy multi-objective optimization is proposed to improve the efficiency of the distribution networks [14]. A step-by-step heuristic algorithm is presented for power loss minimization [15]. Feeder reconfiguration presents an efficient method to optimize practical distribution systems [16]. A method of DGs placement and multi-objective reconfiguration is designed to achieve reactive power losses and the minimum active [17]. A model is established to minimize voltage deviation and the total capacity of reactive power compensation devices, and decrease the system loss. [18]. A multi-objective invasive weed optimization algorithm is proposed for minimization of node voltage deviation, active power loss in distribution network [19]. The DG hosting capacity reconfiguration is designed as a nonlinear, mixed-integer, multi-period optimal power flow and the algorithm is proposed to break-down the large problem size [20]. However, at present, the existent research achievements mainly focus on the methods of multi-objective optimization, which assume that DGs is a constant power PQ model in power flow calculation, and the different DGs influence to the performance has not been studied in detail.

The remainder of this study is organized as follows. Section 3 establishes the multi-agent model and proposes the self-Healing reconfiguration problem formulation and the algorithm. Section 4 discusses the algorithm performance on IEEE 33-bus system. Section 5 summarizes the conclusions.

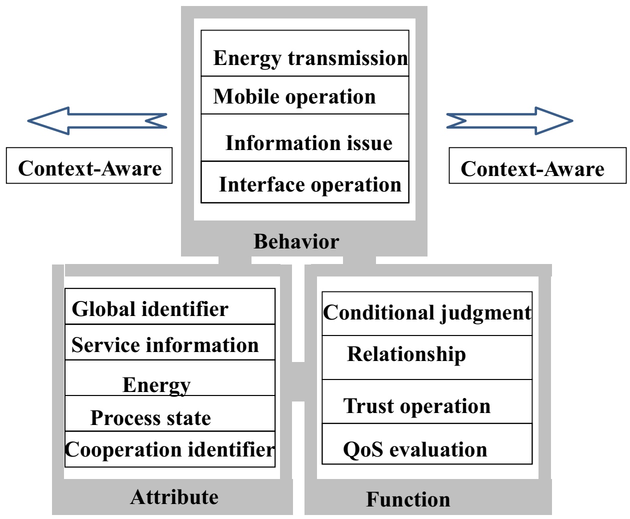

Fig. 1 Self-healing agent

3 Methodology

3.1 Self-healing agent

Self-healing applications should anticipate and respond to system disturbances through the performance of continuous self-assessment to detect, analyze and take corrective actions against dangerous events. The self-healing coordinator agent ensures suitable control decisions to maximize system efficiency and minimize the negative impacts of faults. The decision maker acquires data related to the system state and determines a feasible set of control actions proactively in response to fundamental questions. The agent architecture can be built to manage different aspects of information processing, which sends the control messages to other system agents [21].

Self-healing agent is a micro unit of self-healing service platform by Java. The self-healing agent's working environment is designed as a plug-and-play support system. It has been applied for smart grid, e-service and distribution network service. A self-healing agent designed as three modules (Fig. 1). Attributes describe the characteristic, its include GI (global), CI (cooperation), DS (distribution network service information), PST (process state), and EG (energy). Function is used to evaluate the matching ability to the self-healing agents. It includes QoS evaluation, CJ (conditional judgment) and RL (relationship). Behavior contains IO (interface operation), MP (mobile operation), II (information issue), ET (energy transmission).

Self-healing agent working environment includes network resource service module, network core service module, network service extension module, service plug-in tools. Network resource service module provides the underlying operation to maintain the network platform. In general, agents cannot access containers directly. The container provided registration/cancellation, agents activation/release, resource management, receive/send request. Network core service module, includes service control, agent migration service, evolutionary state management, naming service, community service and monitoring, it also distribute messages to local platform. Network service extension module includes monitoring and management, collection self-healing message (Qos, service reputation, and environment). Service plug-in tools provide the development environment, including the underlying functions development, agent generation, remote collaboration, and negotiation support. Self-healing agent survival environment can be arranged on the Java virtual machine of each service network node as a platform.

In order to present complex distribution network service, communication mechanism is needed. RMI-IIOP is used as protocol for language (NCL) messages. It provides the simplicity of Java RMI and the robustness of CORBA. A NCL message contains a set of arranged parameters randomly. A message is designed as a probe of action so that input and output actions of the other self-healing agent can be funded.

3.2 Power flow calculation of distribution network with DGs

Distributed generation connection leads to the new kinds of nodes appeared in distribution network. Thus, it makes the traditional calculation method of back/forward sweep power flow fail. Improved forward–backward weep method is proposed for power flow calculation of different kinds of node types of distributed generation.

Relationship matrix of bus-injection to branch-current and branch-current to bus-voltage can present based on network topology analysis. According the result of power flow calculation model for distributed generation, the output active and reactive power arc obtained, and the node equivalent injection current model is used as forwarding variable.

The wind turbines are usually asynchronous generator, and magnetic field is mainly created based on absorbing reactive power. The wind turbines are not modeled as PV nodes in PFSs.

$$p = \frac{sR_2U^2}{s^2x^2 + R_2^2} \tag{1}$$

$$s = \frac{R_2(U^2 - \sqrt{U^4 - 4x^2p^2}}{2Px^2} \tag{2}$$

where P is the induction generators active power, s is the induction generators speed slip, U is the generator node voltage, R_2 is the mechanical load equivalent resistance, x is the sum of stator reactance and rotor reactance. The absorbed reactive power Q can be calculated as formula:

$$Q = -\frac{U^2}{X_m} + \frac{-U^2 + \sqrt{U^4 - 4P^2x^2}}{2x} \tag{3}$$

All the DGs units are processed as negative loads and modeled as P–Q (V) nodes. The P–Q (V) nodes active and reactive powers show as follows:

$$\begin{cases} P = -Ps = cons\tan t \\ Q = -f(V) \end{cases} \tag{4}$$

During the calculation process, the voltage at last iteration is used to calculate injected reactive power. The photovoltaic system outputs are converted to grid compatible AC power supplies. There are current control and voltage control. The DGs are modeled as PQ and PV nodes, respectively. The category model:

$$Q = \sqrt{|I|^2 (e^2 + f^2) - p^2} \tag{5}$$

where P is the active power and Q is the distributed generator reactive power respectively. I is the constant injected current, F and E are the node voltage imaginary and real parts. The Formula (5) can be used to obtain the injected reactive power based on the real and imaginary parts of node voltage in the each iteration. The PQ nodes active and reactive powers are as follows:

$$\begin{cases} P = -P_s \\ Q = -Q_s \end{cases} \tag{6}$$

The fuel cells active and reactive powers are obtained based on the inverter parameter $\sin\psi$. The injected reactive and active powers values are described as follows:

$$p = \frac{mU_{Fc}U_s}{X_T}\sin\psi \tag{7}$$

$$Q = \frac{mU_{Fc}U_s\cos\psi}{X_T} - \frac{U_s}{X_T} \tag{8}$$

where U_{Fc} is the fuel cells output DCs voltage, m is the inverter output AC voltage, U_s is the bus voltage of the system. X_T is equivalent reactance of a transformer connected to a fuel cell and a grid. The P and PV nodes node voltage U are described as:

$$\begin{cases} P = -P_s \\ U = U_s \end{cases} \tag{9}$$

The PV node becomes PQ node. Q value is the upper limits or lower of the reactive output power. Micro turbines are modeled as PV nodes as (9).

For the radial distribution network (PV), the method of forward and backward generation is proposed, and a reactive power compensation method is proposed in this paper. N is the number of PV nodes, and DGS injection current is positive. Therefore, the incremental relation between the injected node and the injected voltage can be represented by node simplification. The setting system has a constant type access distribution system, and the reactive power adjustment is carried out according to the following formula:

$$\begin{cases} J\cdot\Delta Q = \Delta U \\ Q^{i+1} = -(Q^i + \Delta Q) \end{cases} \tag{10}$$

where J is $N \times N$ the order sensitivity matrix, the diagonal elements is the sum of all branches reactance from root to node, non-line elements is the reactance sum from two nodes to the root node of the common branch. In fact, the constant type usually gives the upper and lower bound of reactive power, in order to ensure not exceeds the limit, the corrected reactive power equation is as follows:

$$Q^{i+1} = \begin{cases} -Q_{\max} & Q_i + \Delta Q \le -Q_{\max} \\ Q_i + \Delta Q & -Q_{\max} \le Q_i + \Delta Q \le -Q_{\min} \\ -Q_{\min} & Q_i + \Delta Q \ge -Q_{\min} \end{cases} \tag{11}$$

where $Q_{\max}, Q_{\min}$ is PV constant the upper and lower bound of reactive power. Reactive power output can be calculated by active power and the constant current amplitude:

$$Q^{k+1} = \sqrt{I^2(U^k)^2 - P^2} \tag{12}$$

The PQ (V) node belongs to the static characteristic node, which has the characteristics of P (active) and Q (reactive) change with U (node voltage).

$$\begin{cases} P = f_P(U) \\ Q = f_Q(U) \end{cases} \tag{13}$$

Asynchronous wind turbines and synchronous generators without excitation control have this characteristic, so they can be treated as static load nodes. Parallel branches, including parallel capacitors and other components in the model of the ground branch can be treated as a constant impedance model.

3.3 Objective functions and constraints of self-healing reconfiguration

The network self-healing reconfiguration problem is to find a configuration with minimum loss and minimum distributed power loss based on the operating constraints under a certain load pattern. The problem formulation is presented as

$$F_{loss} = \sum_{i=1}^{L_i} r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{14}$$

F_{loss} is the active power loss membership function, r_i is the resistance of the branch i. V_i represents the branch i node voltage. P_i, Q_i are terminal active and reactive power. L_i is the branches number. Voltage variation may be due to changes in DGS output.

Another objective function is the minimum distributed power loss. Distributed generation loss refers to the amount of power generated by the distributed power supply due to power constraints, which is

$$F_{pdg} = \min \sum_{i=1}^{N_{DG}} (P_{DGMax,i} - P_{DG,i}) \tag{15}$$

where, N_{DG} is the number of DG access nodes, $P_{DGMax,i}$ is the upper limit of the i DG output active power, $P_{DG,i}$ is the active power.

The multi-objective optimization model is constructed to maximize the satisfactions of different objectives based on the evaluation functions. The model is represented as:

$$\begin{aligned}
&Min(Mep(F_{loss}), Mep(F_{pdg})) \\
&Subject \\
&\begin{cases}
V^{\min} \le V_i \\
V_i \le V^{\max} \\
k_i\,|I_i| \le I_i^{\max} \\
k_i\,|P_i| \le P_i^{\max} \\
P_i - V_i \sum\limits_{j=1}^{N_{bus}} V_j Y_{ij} \cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \\
Q_i - V_i \sum\limits_{j=1}^{N_{bus}} V_j Y_{ij} \sin\left(\delta_i - \delta_j - \theta_{ij}\right) = 0
\end{cases}
\end{aligned} \tag{16}$$

which $Mep(F)$ is the value to evaluate F, and network technical constraints is showed:
(1) Power balance

$$P_i - V_i \sum_{j=1}^{N_{bus}} V_j Y_{ij} \cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \tag{17}$$

$$Q_i - V_i \sum_{j=1}^{N_{bus}} V_j Y_{ij} \sin\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \tag{18}$$

(2) Bus voltage operating limit.

$$V^{\min} \le V_i \le V^{\max} i = 1, 2, \ldots, N_{bus} \tag{19}$$

(3) Line current limit.

$$k_i\,|I_i| \le I_i^{\max} \quad i = 1, 2, \ldots, N_s \tag{20}$$

(4) Line power limit, as formulated below

$$k_i\,|P_i| \le P_i^{\max} \quad i = 1, 2, \ldots, N_s \tag{21}$$

(5) Radiality of distribution network.

$$N_{br} = N_{bus} - 1. \tag{22}$$

3.4 A self-adaptive differential evolution algorithm with improved strategies

The aim of a power system reconfiguration optimization is to find a solution, in Formula (16), constraint function is very complex. The problem is a global optimization problem, namely, covariance matrix adaptation evolution strategies, differential evolution (DE) [22–25]. In general, the faster convergence leads to local optimum, it can be overcome by using a larger population size. In this paper, we present the Self-Adaptive Differential Evolution Algorithm with Improved Strategies (SDEI) to solve the problem. SDEI has extended from the original algorithm of DE. The basic operations are illustrated as follows.

Definition 1 (*Pareto dominance*): $u = (u_1, u_2, \ldots u_n)$ is dominate $v = (v_1, v_2, \ldots v_n)$, iff μ is partially less than v, $\forall i \in \{1, \ldots, n\}, u_i \le \quad vi \wedge \exists i \in \{1, \ldots, n\} : ui < vi$.

Definition 2 (*Pareto optimality*): $x \in X$ is pareto optimal to X iff not $x\prime \in X$ for which $v = f(x\prime) = (f_1(x\prime), \ldots, f_n(x\prime))$ dominates $u = f(x) = (f_1(x), \ldots, f_n(x))$.

Definition 3 X is a non-dominated individual, and Y is a dominated individual, $X \succ Y$, "$\succ$" denotes the dominated-relation. $\forall X, Y \in Pop$, X relates with Y, iff $X \succ Y$ or $X = Y$; otherwise there is no relation between X and Y.

Definition 4 $\forall X, Y \in PopX >_d Y$ iff $X \succ Y$ or X does not relate with Y. A partial order $\ge$ n is defined as, irank represents Non-domination rank, and idistance represents local crowding distance. I $\ge$ n j if (irank $<$ jrank) or ((irank = jrank) and (idistance $>$ jdistance)).

The SDEI structure is a parallel search algorithm. It uses N vectors of the decision parameters. There are four operators for the algorithm, namely, mutation, crossover, selection and migrating in order to obtain more accurate approximations.

Stage 1. The initial population X_0^i is selected randomly and it covers the entire search space uniformly:

$$X_0^i = x_{\min} + \rho_i\,(x_{\max} - x_{\min}) \tag{23}$$

where i = 1, 2...N. ρ_i is a uniformly distributed random number. $x_{\max}$ is the lower bound and $x_{\min}$ is upper bound of the decision parameters.

Stage 2. For each i = 1 ...N, a new mutant vector V_{G+1}^i is generated by combining vectors from the current population. A mutant individual V^i_{G+1} is generated according to the following equations

$$V^i_{G+1} = X^{best}_G + \mu\left(X^{r1}_G - X^{r2}_G\right) \tag{24}$$

where X^{best}_G denotes the best individual; $\mu > 0$ is mutation constant parameter, which controls the difference amplification between two individuals; and r1, r2 $\in \{1, 2, \ldots, N\}$. An adaptive setting rule shows in (25)

$$t = e^{1-\frac{N_m}{N_m+1-N}} \tag{25}$$

$$\mu = \mu_0 * 2^t \tag{26}$$

where μ_0 is initial mutation operator. N indicates the current evolution number. N_m denotes the maximum fitness evaluation number. At the beginning, the adaptive mutation operator is carried out with a probability within $[\mu_0 - 2\mu_0]$ to maintain the diversity. Along with the evolution lapse, mutation operators are gradually reduced to retain good information and expect good balance.

Stage 3. In order to increase next population diversity, an offspring is reproduced by the crossover operation. For j = 1, 2 … n, a random number rand1 ∈ [0, 1] is generated.

If rand1 is smaller than the predefined crossover constant, CR ∈ [0, 1], the jth mutant vector becomes the jth trial vector component V^i_{G+1}. Otherwise, the jth target vector X^{ij}_G is selected as the jth trial vector component.

$$U^i_{G=1} = \left(u^{i1}_{G+1,} u^{i2}_{G+1,} \ldots u^{in}_{G+1}\right) \tag{27}$$

$$u^{ij}_{G+1} = \begin{cases} v^i_{G+1} & if \quad rand1 \le \quad CR \quad or \quad j = rnbr(i) \\ x^{ij}_G & if \quad rand1 > CR \quad or \quad j \ne rnbr(i) \end{cases}$$

Cross probability factor CR affects convergence speed, a higher value of difference vector magnitude tends to global exploration, but the convergence rate is slow, otherwise it is to local search, the convergence rate is faster, but easy to the non-optimal solution. In the initial stage, the CR is small, which is help to improve the global capability, and then accelerate the convergence by using larger CR. Open up Parabolic model is adopted to incremental method of crossover probability factor.

$$CR = CR_{\min} + (CR_{\max} - CR_{\min})\,(j/J_{\max})^2 \tag{28}$$

where $rnbr(i)$ is a randomly chosen index $\in \{1.2.3\ldots n\}$. $rand1$ is the jth uniform random number generator evaluation ∈[0, 1]. $J_{\max}$ represents the maximum iterations number, $CR_{\max}$ is 0.9, $CR_{\min}$ is 0.2.

Stage 4. At the selection step, the crossover trial vector is used for the next generation, only when the target function value decreases with respect to the previous vector,

$$X^i_{G+1} = \begin{cases} U^i_{G+1}\ if \quad R\left(U^i_{G+1}\right) > R\left(X^i_G\right) \\ X^i_G \quad otherwise \end{cases} \tag{29}$$

Stage 5. However, faster descending usually brings a local minimum or the next better individuals are not reproduced by the mutation and crossover operations to clustered individuals. New population can be regenerated by the migrating operation. The new candidates are chosen based on the best individual X^i_{G+1}. The jth gene of the ith individual is therefore regenerated by.

$$X^j_{G+1} = \begin{cases} X^{best}_G + rand2_{ij}\left(X^{\min}_G - X^{best}_G\right) & if\ \overline{rand2} \ge \frac{X^{best}_G - X^{\min}_G}{X^{\max}_G - X^{\min}_G} \\ X^{best}_G + rand2_{ij}\left(X^{\min}_G - X^{best}_G\right) & otherwise; \end{cases} \tag{30}$$

where $rand2_{ij}, \overline{rand2_{ij}} \in [0, 1]$ is the jth uniform random number generator evaluation, $X^{\min}_G$ and $X^{\max}_G$ are the lower and upper bounds of the jth decision parameters gene. Only if population diversity matches the desired tolerance, the migrating operation is performed. The measure ρ_m is defined as,

$$\rho_m = \frac{\sum\limits_{i=1}^{N} \sum_{j=1}^{n} \eta_{ji}}{n(N-1)} < \varepsilon_1 \tag{31}$$

where

$$\eta_{ji} = \begin{cases} 1, & if \left|\left(X^i_G - X^{best}_G\right)/X^{best}_G\right| > \varepsilon_2 \\ 0 & otherwise \end{cases}$$

where ε_1 and ε_2 are the desired tolerance for the population and the gene diversity to the best individual. Here, η_{ji} is a gene diversity index. Zero means that the jth gene closely clusters to the best individual. If population diversity degree is smaller than the tolerance ε_1, the migrating operation is performed.

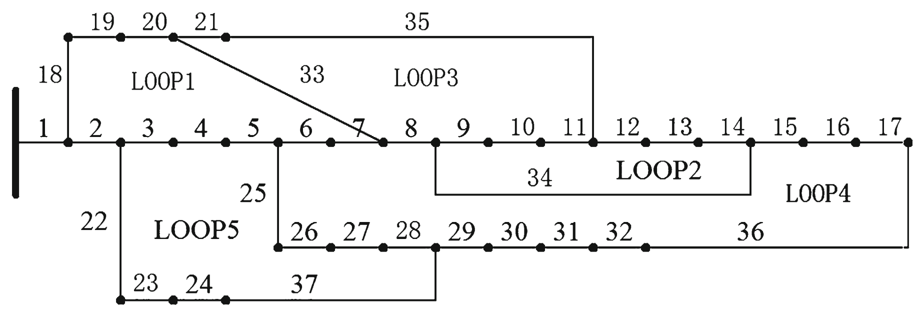

Fig. 2 IEEE 33-bus distribution network system

4 Result analysis and discussion

The results of proposed method are obtained to evaluate its effectiveness on IEEE 33-bus radial distribution systems, the system is a 32 bus test system, it has 5 tie switches and 12.66 kV consists of 32 sectionalizing,the test system is as shown in Fig. 2. The initial active power loss is 202.67 kW before reconfiguration. Data is presented in Table 1 for IEEE 33-bus network system [26].

Two kinds of renewable distributed power supply are used in the system, wind turbine and photovoltaic power. The output power is characterized with wind speed and light intensity changes. This test is designed several schemes to analysis influence for different DG models. DG installation location and installed capacity as shown in Tables 2 and 3.

Test case 1, Suppose DG1 is placed in bus7, DG2 in bus14, DG3 in bus24, DG4 in bus30. DG1 and DG3 are wind turbine, DG2 and DG2 are PV. Test case 2, suppose DG1 is placed in bus5, DG2 in bus23, DG3 in bus28. DG1 is wind turbine, DG2 and DG3 are PV.

Tables 4 and 5 show the results of multi-objective optimization algorithm with 4 DG. In the table, a set of the Pareto solutions is shown based on the proposed method. The results of single objective optimization and optimal compromise value are presented in Table 5. Power losses minimum value is 0.06, and then DG output losses value is 0.12, DG output losses minimum value is 0.08, and then power losses minimum value is 0.161. In fact, the single-objective optimization value cannot be the optimization solution in the final repository. The optimal compromise value is 0.112 (power losses) and 0.966 (DG output losses).

The results show that the optimal solution can be obtained by this method. Similarly, Tables 6 and 7 show the multi-objective optimization results of 3 DG in test case 2. Power losses minimum value is 0.0273, and then DG output losses value is 0.14, DG output losses minimum value is 0, and then power losses minimum value is 0.0773 in the single-objective optimization. The optimal compromise value is 0.0301 (power losses) and 0.0254 (DG output losses), which can achieve the optimal solution of the maximum DC output function.

It can be seen from Tables 4, 5, 6, and 7, the access of DG greatly reduces the network loss of the system, the loss of optimal compromise solution is reduced by 52%, and the DG utilization rate is 95.1%, and the reactive power is also been fully utilized. In the view of the switch open and close combination, the compromise solution can expand distributed power supply range. It shows that distributed power supply has an important role to power supply capacity. The 33 bus voltage file (before and after refactoring) is shown in Fig. 3. By reconfiguring the DGS, it is much better than the initial network.

5 Conclusion

This study examines a core problem in the design of self-healing reconfiguration scheme. Base on the multi-agent systems, multiple objectives are considered for minimum distributed generation output loss, load balancing among the feeders, minimum power loss, and a self-adaptive differential evolution algorithm with improved strategies is proposed to solve optimization problem. The following conclusions could be drawn:

(1) Multi-agent system concepts are proposed to develop a self-healing strategy, self-healing agent is designed to aware the current network state and work cooperatively, it should anticipate and respond to system disturbances through the performance of continuous self-assessment to detect, analyze against self-healing events. Service request is achieved by service composition of self-healing agents.
(2) Improved forward-backward weep method is used to achieve power flow solution for different node types of distributed generations. The flow calculation models are constructed respectively according to the different features of PV nodes. PI nodes and PQ (V) nodes, which can effectively solve the power flow problem with different distributed power generation.
(3) Multiple objectives of self-healing reconfiguration are designed for load balancing among the feeders, minimum distributed generation output loss, minimum power

Table 1 Test data for IEEE 33-bus distribution network system

S. no.	From bus (i)	To bus (i+1)	R (i,i+1)	X (i, i+1)	P (kW)	Q (kW)
1	0	1	0.0922	0.4	100	60
2	1	2	0.0493	0.2511	90	40
3	2	3	0.366	0.1864	120	8
4	3	4	0.3811	0.1941	60	30
5	4	5	0.819	0.707	60	20
6	5	6	0.1872	0.6188	200	100
7	6	7	0.7114	0.2351	200	100
8	7	8	1.03	0.74	60	20
9	8	9	1.044	0.74	60	20
10	9	10	0.1966	0.065	45	30
11	10	11	0.3744	0.1238	60	35
12	11	12	1.468	1.155	60	35
13	12	13	0.5416	0.7129	120	80
14	13	14	0.591	0.526	60	10
15	14	15	0.7463	0.545	60	20
16	15	16	1.289	1.721	60	20
17	16	17	0.723	0.574	90	40
18	1	18	0.164	0.1565	90	40
19	18	19	1.5042	1.3554	90	40
20	19	20	0.4095	0.4784	90	40
21	20	21	0.7089	0.9373	90	40
22	2	22	0.4512	0.3083	90	50
23	22	23	0.89	0.7091	420	200
24	23	24	0.896	0.7011	420	200
25	5	25	0.203	0.1034	60	25
26	25	26	0.2842	0.1447	60	25
27	26	27	1.059	0.9337	60	20
28	27	28	0.8042	0.7006	120	70
29	28	29	0.5075	0.2585	200	600
30	29	30	0.9744	0.963	150	70
31	30	31	0.3105	0.3619	210	100
32	31	32	0.341	0.5302	60	40
33	7	20	2	2	–	–
34	8	14	2	2	–	–
35	11	21	2	2	–	–
36	17	32	0.5	0.5	–	–
37	24	28	0.5	0.5	–	–

Table 2 DGs parameters of test case 1 (4 DG)

Bus no.	DG type	Capacity (kW)	Max reactive power (kVar)	Min reactive power (kVar)
7	Wind turbine	200	160	−120
14	PV	100	80	−60
24	Wind turbine	200	160	−120
30	PV	200	160	−120

Table 3 DGs parameters of test case 2 (3DG)

Bus no.	DG type	Capacity (kW)	Max reactive power (kVar)	Min reactive power (kVar)
5	Wind Turbine	200	160	−120
23	PV	100	80	−60
28	PV	100	80	−60

Table 4 The non-dominated solutions results of test case 1 (4DGs)

Pareto no.	States of the switches	Power losses (kW)	Voltage deviation (pu)	DG output (MW)
1	11, 14, 28, 33, 34	0.06	0.986	0.16, 0, 0.17, 0.15
2	9, 14, 28, 32, 33	0.119	0.951	0.14, 0, 0.15, 0.13
3	10, 28, 32, 33, 34	0.142	0.9666	0.038, 0.065, 0.047, 0.029
4	9, 28, 32, 33, 34	0.118	0.971	0.035, 0.085, 0.045, 0.026
5	10, 14, 28, 32, 34	0.131	0.951	0.18, 0.1, 0.17, 0.17
6	11, 14, 28, 33, 34	0.07	0.956	0.17, 0.02, 0.15, 0.18
7	9, 14, 32, 33, 34	0.117	0.951	0.04, 0.09, 0.05,0.03
8	10, 28, 32, 33, 34	0.139	0.9596	0.04, 0.072, 0.032, 0.024
9	9, 14, 28, 32, 33	0.117	0.974	0.031, 0.082, 0.065, 0.036
10	10, 28, 32, 33,34	0.121	0.951	0.14, 0.08, 0.14, 0.13

Table 5 Final reconfiguration results of test case 1 (4DG)

Pareto optimization goal	States of the switches	Power losses (kW)	Voltage deviation (pu)	DG output (MW)
Power losses minimum value	11, 14, 28, 33, 34	0.06	0.986	0.16, 0, 0.17, 0.15
DG output losses minimum value	9, 14, 28, 32, 33	0.131	0.951	0.18, 0.1, 0.17, 0.17
Optimal compromise value	10, 28, 32, 33, 34	0.112	0.966	0.14, 0.09, 0.15, 0.13

Table 6 The non-dominated solutions of test case 2 (3DG)

Pareto no.	States of the switches	Power losses (kW)	Voltage deviation (pu)	DG output (MW)
1	18, 21, 34, 36, 37	0.05	0.986	0.188, 0.092, 0.09
2	14, 27, 33, 35, 36	0.048	0.961	0.189, 0.093, 0.081
3	14, 28, 33, 35, 36	0.03	0.9566	0.189, 0.091, 0.08
4	18, 21, 34, 36, 37	0.06	0.953	0.179, 0.091, 0.081
5	14, 27, 33, 35, 36	0.0301	0.9666	0.1746, 0.1, 0.1
6	14, 28, 33, 35, 36	0.0273	0.986	0.13, 0.06, 0.07
7	18, 21, 34, 36, 37	0.0267	0.976	0.191, 0.088, 0.083
8	18, 21, 34, 36, 37	0.047	0.979	0.193, 0.092, 0.093
9	14, 27, 33, 35, 36	0.046	0.965	0.192, 0.093, 0.092
10	18, 21, 34, 36, 37	0.0773	0.951	0.2, 0.1, 0.1

Table 7 Final reconfiguration results of test case 2 (3DG)

Pareto optimization goal	States of the switches	Power losses (kW)	Voltage deviation (pu)	DG output (MW)
Power losses minimum value	14, 28, 33, 35, 36	0.0273	0.986	013, 0.06, 0.0 7
DG output losses minimum value	18, 21, 34, 36, 37	0.0773	0.951	0.2, 0.1, 0.1
Optimal compromise solution	14, 27, 33, 35, 36	0.0301	0.9666	0.1746, 0.1, 0.1

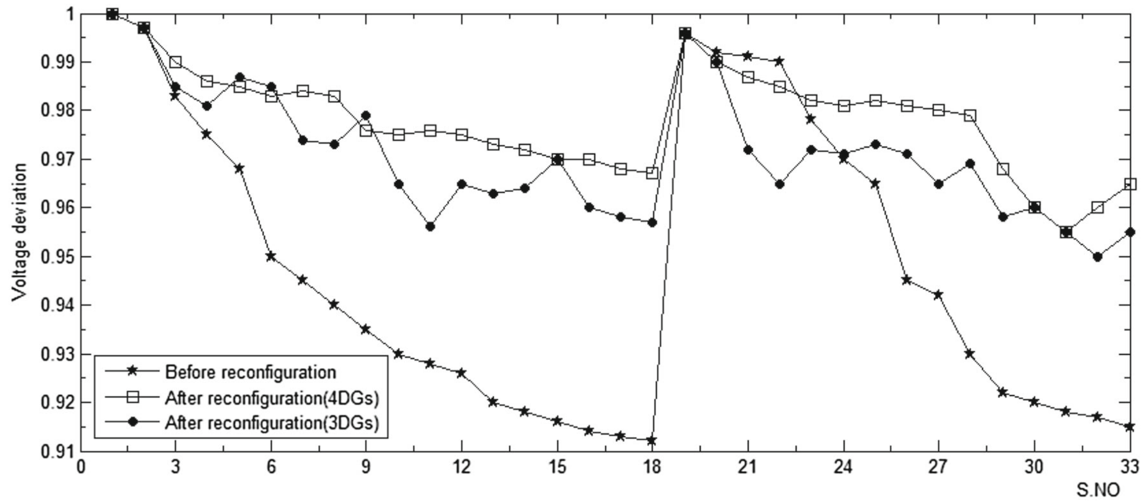

Fig. 3 Voltage deviation of IEEE 33-bus distribution network system

loss and branch current constraint violation, and a self-adaptive differential evolution algorithm with improved strategies is proposed to solve optimization problem. The performance of proposed algorithm is analyzed for different case studies on IEEE 33-bus system. The simulation results show that the approach can significantly improve the self-healing reconfiguration performance.

In the case of distributed network failure, the solution of islanding self-healing reconstruction is another focus of further research. With the DGs development, the distribution network has changed from a single network to an active distribution network, which is an urgent question: how to effectively use the island DGs, and put forward the corresponding failure recovery strategy.

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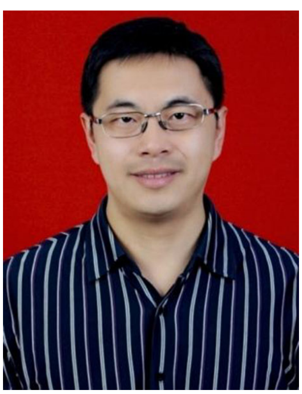

Sun Hongbin is a Professor at the College of Information Sciences and Technology, Changchun Institute of Technology, he obtained his B.S. and M.S. in Electrical Engineering from Huabei Electric University, China in 1991, 1997, respectively. He obtained his Ph.D. in Electrical Engineering from Donghua University, Shanghai, China in 2007. His current research interests include complex network systems, nature-inspired technologies, smart-grid technologies and multi-agent systems

Zhang Yong obtained his B.S., M.S. and Ph.D. degrees in Electrical Engineering from dongbei University, Shenyang, China in 1994, 1999 and 2003, he is currently an associate Professor with the College of Control Science and Engineering, Jilin University, China. His research interests include distribution automation, distribution system planning, and smart grids.

Hu Bin obtained his B.S., M.S. degrees in Electrical Engineering from Jilin University, Jinlin, China in 2009 and 2013, he is currently working toward the Ph.D. degree in electrical at department of electrical Engineering, Texas A&M University, He His scientific interests include computational intelligence, network intelligence, intelligent decision-making.