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A Fast Restoration Strategy in Distribution Systems Using an Enhanced Differential Evolution Approach

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A Fast Restoration Strategy in Distribution Systems Using an Enhanced Differential Evolution Approach*

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Abstract

This paper proposes a fast restoration strategy of distribution systems using an enhanced differential evolution (EDE) approach. Service restoration of distribution systems is an emergent task that must be performed rapidly by the system operators. Basically, it is a complicated combinatorial optimization problem, often having many candidate solutions to be evaluated by the operators. To improve the efficiency of restoration and reduce the burden on the operators, this paper proposes an EDE method combining variable scaling differential evolution (VSDE) algorithm and ant system (AS) to solve the combinatorial optimization problem. To verify the effectiveness of the proposed method, a typical distribution system of the Taiwan Power Company (TPC) was tested and compared with the existing methods. The results show the proposed method was superior to the existing methods in terms of convergence time and the obtained restoration plan.

KEYWORDS: service restoration, enhanced hybrid differential evolution, ant system, distribution engineering

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1. Introduction

Service restoration is an emergent task in the operation of distribution systems. When a fault occurs, the blackout area and the number of customers affected heavily depend on the effectiveness of the service restoration algorithm. Generally, the TPC operators tend to restore the electricity power based on of their existing knowledge and heuristic rules. However, owing to the multitude of feeders, laterals, and switches in a typical distribution system, it is not easy to restore an out-of-service area solely depending on the past experiences of human operators. Therefore, how to devise a rapid and effective restoration plan is of major concern in this paper.

Much research has been developed to deal with the problems of service restoration. The heuristic-based approach [1] has been developed by the operators at many utilities including those of TPC to reach a proper restoration plan in a short period. Since the heuristic rules are often expressed in imprecise linguistic terms, the fuzzy reasoning approach [2]-[3] was proposed to achieve an efficient inference for the problem of service restoration. To deal with the problem of service restoration with many conflicting objectives, the multi-objective functions with fuzzy and non-fuzzy reasoning approaches were presented in [4]-[7].

Traditionally, the techniques mentioned above can serve as useful tools to reach a proper restoration plan. However, because of the many switches in a typical distribution system, the related inference programs may stall at the local optimal solutions, leading to an unsatisfactory restoration plan. Furthe, the related inference approaches still have the problem of slow convergence during the optimization process.

In this paper, an EDE algorithm was presented to solve the problem of multi-objective service restoration of distribution systems. The proposed EDE combines variable scaling DE algorithms [8]-[9] and ant systems [10] to reach an effective and rapid restoration of distribution systems. By simulating the natural evolutionary process, the classical DE has the advantages of rapid convergence and easy implementation. To have the classical DE escape from local minima, a variable scaling mutation operation using the 1/5 success rule of evolution strategies [9] is utilized in this paper. To further enhance the global search ability of DE, an ant system was then used to replace the *selection* operation in DE. Based on rapid convergence and global search ability, EDE can offer a higher probability of converging toward the global solution than existing methods.

2. Objective Functions

Service restoration of a distribution system is a complex and urgent task that must be performed rapidly by system operators. In this paper, we focus the objectives of the restoration plan on the following concerns: 1) restore as much load within the out-of-service area as possible, 2) operate a minimal number of switches, 3) devices should not overload too much, and if they must, and 4) keep the load balanced as much as possible. Other issues such as maintaining the radial system structure and voltage drop are considered as system constraints. The definitions below are the fuzzy objectives and their associated membership functions.

(1) *Load Restoration* (*LR*) *Objective*

The load restoration objective considered in this paper is to restore as much load within the out-of-service area as possible. As depicted in Fig. 1(a), the associated membership function is denoted as

$$\mu_1 = \begin{cases} 1, & if\ R_L = R_{LA} \\ R_L / R_{LA}, & if\ 0 < R_L < R_{LA} \\ 0, & if\ R_L = 0 \end{cases} \tag{1}$$

where R_L represents the amount of loads actually restored and R_{LA} means the amount of total lateral loads in the out-of-service area. Note, the case of $R_L > R_{LA}$ does not exist in the restoration plan.

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(2) *Switches Operation* (*SO*) *Objective*

The second objective is to operate a minimal number of switches. A decreasing membership function, as shown in Fig. 1(b) for lateral (or feeder) switches, is utilized as follows.

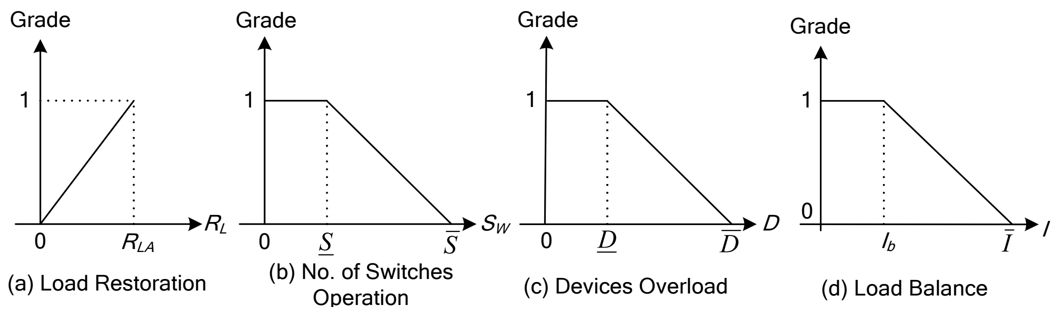

Fig. 1 The membership functions of the four objectives.

$$\mu_2 = \begin{cases} 1, & if\ S_W \le \underline{S} \\ 1 - \dfrac{S_W - \underline{S}}{\overline{S} - \underline{S}}, & if\ \underline{S} < S_W < \overline{S} \\ 0, & if\ S_W \ge \overline{S} \end{cases} \tag{2}$$

where S_W is the total number of switches operation, $\underline{S}$ and $\overline{S}$ are the possible minimal and maximal number of switches operation, respectively.

(3) *Devices Overload* (*DO*) *Objective*

Since a light overload is rather common in the daily operation of TPC, the associated membership function of devices overload, including the supporting feeders and laterals, is depicted in Fig. 1(c) which can be expressed as

$$\mu_3 = \begin{cases} 1, & if\ D \le \underline{D} \\ 1 - \dfrac{D - \underline{D}}{\overline{D} - \underline{D}}, & if\ \underline{D} < D < \overline{D} \\ 0, & if\ D \ge \overline{D} \end{cases} \tag{3}$$

where D represents the actual load of one particular device (feeder or lateral), $\underline{D}$ is the capacity of the devices, $\overline{D}$ is the maximal allowable overload (in Amperes). If several devices are overloaded, including the supporting feeders and supporting laterals, the resulting membership function is the one obtained by the *AND*-operation of all corresponding membership functions.

(4) *Load Balance* (*LB*) *Objective*

The forth objective is to keep the load balance on the devices as much as possible to relieve the overloads in the distribution system. The associated membership function of the load balance objective, as shown in Fig. 1(d), is defined to show the degree of current variation for one device as follows.

$$\mu_4 = \begin{cases} 1, & if\ I \le I_b \\ 1 - \dfrac{I - I_b}{\bar{I} - I_b}, & if\ I_b < I < \bar{I} \\ 0, & if\ I = \bar{I} \end{cases} \tag{4}$$

where I_b is the device current before restoration and I denotes the maximal allowable current capacity. The *AND*-operation is also used to attain the resulting membership function among all of the corresponding membership functions.

Based on the fuzzy objective as well as their corresponding membership functions described above, the weighted-sum strategy is utilized to determine the fuzzy objective value of the ith feasible solution as follows.

$$\underset{i \in \Psi}{Max}\ \tilde{\mu}_i = \sum_{k=1}^{4} w_k \times \mu_k \tag{5}$$

where Ψ denotes the set of feasible solutions for each optimization process, w_k is the weighting value of the kth objective, and μ_k means the membership function of the kth objective.. The optimal decision is the one with the largest fuzzy objective value in the solution domain. Note, determining of a rational weighting value w_k in (5) is important for the system operators. In this paper, the analytical hierarchy process (AHP) method [11] is used to help the operators obtain the weighting value of each objective.

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3. The Proposed Enhanced Differential Evolution Algorithms

Based on the basic evolutionary strategies, EDE achieves the fittest individual after repeated initialization, mutation, recombination, and selection operations. The general scheme of the EDE algorithm is described as follows.

(1) *Initialization*

Let $p_i=[p_{i1}, p_{i2}, \ldots, p_{iM}]$ be a trial vector representing the ith individual ($i=1, 2, \ldots, P$) of the population to be evolved, where P is the population size and M is the dimension of each individual. The elements in vector p_i represent the decision variables (genes) which are randomly generated as follows.

$$p_{ij} = p_{ij,\min} + \sigma \times (p_{ij,\max} - p_{ij,\min}), \quad j = 1,\ 2,\ \ldots,\ M \tag{6}$$

where p_{ij} represents the jth gene of the ith individual, $p_{ij,min}$ and $p_{ij,max}$ mean the lower and upper bounds of p_{ij}, respectively; and σ represents the uniform random number between 0 and 1.

(2) *Variable Scaling Mutation*

The mutation operation of classical DE is performed by adding a differential vector to the parent individual as follows.

$$p_i' = p_i + f_m \times (p_{i_a} - p_{i_b}) \tag{7}$$

where p_{i_a} and p_{i_b} are the randomly selected individuals in the parent population, $(p_{i_a} - p_{i_b})$ is a differential vector, and $f_m \in [0,1]$ represents the mutation factor.

As shown in (7), DE uses a fixed mutation factor to increase the diversity of the population. In general, a smaller mutation factor requires more computational time while the larger one may result in falling into local minima. Therefore, the selection of a mutation operator is a very important issue in DE. In this paper, the variable scaling mutation (VSM) based on the 1/5 success rule [9] is used to overcome the drawback of the fixed mutation factor method. The VSM varies the mutation factor according to the frequency of successful mutations to avoid falling into local minima and save more computational time. The rule of updating mutation factor is as follows.

$$f_m(t+1) = \begin{cases} k_d \times f_m(t), & if\ \ p_s(t) < 1/5 \\ k_i \times f_m(t), & if\ \ p_s(t) > 1/5 \\ f_m(t), & if\ \ p_s(t) = 1/5 \end{cases} \tag{8}$$

where $p_s(t)$ is the frequency of successful mutations. The successful mutations defines the fuzzy objective value (as shown in (5)) of the best individual in the next generation as being better than the best individual in the current generation. The factor k_d is set at 0.85 and k_i is the reciprocal of k_d in this paper.

As shown in (8), if the frequency of successful mutations is less than one fifth, the mutation factor of the next generation is changed to a smaller value to search for better individuals. On the other hand, if the frequency of successful mutations is larger than one fifth, a larger mutation factor is obtained for the next generation to speed up the optimization processes.

(3) *Recombination*

In essence, the mutant individual in (7) is a noisy replica of p_i. When the population diversity is small, the candidate individuals will rapidly gather together so the individuals cannot be further improved. To extend the local diversity of the mutant individuals, a recombination operation is introduced as follows.

$$p_{ij}' = \begin{cases} p_{ij}, & if\ rand_{ij} > R_r \\ p_{ij}', & if\ rand_{ij} \le R_r \end{cases} \tag{9}$$

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where p_{ij} is the jth gene of the ith individual before mutation, p_{ij}' represents the jth gene of the ith offspring individual following mutation, $rand_{ij}$ is a random number with normal distribution, and $R_r \in [0,1]$ is a recombination factor. Equation (9) indicates each gene of the ith individual is reproduced from the current gene p_{ij} or the mutant gene p_{ij}'.

(4) *Selection*

Each offspring individual must compete against its parent individual based on the fuzzy objective values as follows.

$$p_i'(t+1) = \begin{cases} p_i(t+1), & if\ \tilde{\mu}_i(t+1) > \tilde{\mu}_i(t) \\ p_i(t), & otherwise \end{cases} \tag{10}$$

where $\tilde{\mu}_i(t+1)$ and $\tilde{\mu}_i(t)$ represent the fuzzy objective values of the ith individual at t+1 and t iteration, respectively. As shown in (10), it is observed any parent individual will be replaced by its offspring individual if the fuzzy objective value of the parent individual is worse than that of its offspring individual.

As described above, the classical DE used one-to-one competition to retain its offspring, giving rise to a rapid convergence rate. This rapid convergence may lead to a higher probability of obtaining a local optimum because the diversity of the population descends more rapidly during the optimization process. To increase the global search ability, an AS method is utilized to replace the *selection* operation in the classical DE algorithm.

The AS was first applied to the traveling salesman problem [10]. Informally, ants prefer to move to cities which are connected by short distance with a high amount of pheromone. However, the cities with short distance and high pheromone are not absolutely selected by ants. Each ant generates a complete tour by choosing the cities according to a probabilistic state transition rule as follows.

$$\Pr_i(t) = \frac{[\tau_i(t)]^{\gamma}[\tilde{\mu}_i]^{\psi}}{\sum_{i=1}^{P}[\tau_i(t)]^{\gamma}[\tilde{\mu}_i]^{\psi}} \tag{11}$$

where $\tau_i(t)$ is the pheromone concentration of the ith ant at tth iteration, $\tilde{\mu}_i$ is the fuzzy objective value shown in (5), γ and ψ are the weighting constants of the pheromone and fuzzy objective value, respectively.

In addition, the pheromone concentration is updated according to the following formula:

$$\tau_i(t+1) = \rho\tau_i(t) + \Delta\tau_i \tag{12}$$

where

$$\Delta\tau_i = \begin{cases} \dfrac{q}{d_i}, & \textit{if ith ant is better so far} \\ 0, & \textit{otherwise} \end{cases} \tag{13}$$

$0<\rho<1$ is a pheromone decay parameter, q is a constant, and d_i is the Euclidean distance. In this paper, d_i is the reciprocal of $\tilde{\mu}_i$.

(11) to (13) show if the fuzzy objective value of the offspring individual is better than the other individuals, the pheromone concentration τ_i is increased and it has more probability of surviving as a new individual in the next generation. Compared to the one-to-one competition method, the probabilistic state transition rule has the advantages of retaining the diversity of the population and escaping from local optimal solutions.

4. Search of the Best Restoration Plan Using EDE

The proposed EDE algorithm for searching the best restoration plan is described in the following steps:

Step 1: Obtain the weighting vector using the AHP method.

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Step 2: Randomly generate the initial parent trial vector p_i, $p_i = [p_{i1}, p_{i2}, ..., p_{ij}, ..., p_{iM} | p_{i,TSW}]$, where p_{ij} represents the state of either 0 or 1 of the supporting lateral switch and $p_{i,TSW}$ is the state of the supporting feeder tie-switch. The elements of p_{ij} can be obtained by modifying (6) as follows.

$$p_{ij} = round\,(\sigma \times (p_{ij,\max} - p_{ij,\min})), \quad j = 1,\ 2,\ ...,\ M \tag{14}$$

where $round(\bullet)$ means the nearest integer for the real number. The values of $p_{ij,min}$ and $p_{ij,max}$ are set at 0.1 and 0.9, respectively.

Step 3: Evaluate the fuzzy objective value of each parent individual using (5).

Step 4: Execute the variable scaling mutation and recombination operations according to the variable mutation factor f_m and recombination factor R_r, as described in (8) and (9), respectively.

Step 5 For each offspring individual, modify its genes into the value of either 0 or 1 as follows.

$$p_{ij}^{'} = round(f(p_{ij})) = round\left(\frac{1-e^{-2\delta p_{ij}}}{1+e^{-2\delta p_{ij}}}\right) (i=1, 2, \ldots, P; j=1, 2, \ldots, M) \tag{15}$$

where $f(\bullet)$ is a hyperbolic tangent sigmoid function [12] which limits the gene p_{ij} to the range between 0 and 1 and δ is the slope parameter.

Step 6: Proceed to calculate the fuzzy objective value of each offspring individual as described in (5).

Step 7: Utilize the AS method described in (11)~(13) to select P sets of the better individuals in the population.

Step 8: Repeat steps 4 to 7 until the optimization process is converged or the maximum iteration is reached. The solution with the highest fuzzy objective value is chosen as the best restoration plan in the population.

5. Simulation Results

To demonstrate the performance of the proposed method, a typical TPC 11-22kV distribution system, as shown in Fig. 2, is utilized in this paper. The combinatorial optimization process was implemented using the commercial MATLAB package. For comparison, the heuristic-based fuzzy (HBF) method [2] and DE algorithm [8] are also tested using the same database.

As shown in Fig. 2, suppose one fault took place at point *J* located at feeder YD28. The circuit breaker CB2 was then tripped and the faulted zone was isolated, leaving lateral loads from LAT1 to LAT9 out-of-service. Our goal is to restore the nine lateral loads using the supporting feeder YE29 and eight supporting laterals of LAT10 to LAT17. Since LAT9 is not equipped with a supporting lateral, it must be supplied power from the supporting feeder YE29. In addition, if the power of the *i*th lateral load is supplied from its supporting lateral, the normally-open lateral switch SWi must be closed while the corresponding normally-closed lateral switch $\overline{\mathrm{SWi}}$ must be opened.

5.1 Parameters Setting

As shown in Fig. 1, four objectives including load restoration, switches operation, devices overload, and load balance are considered. Since there are nine lateral loads to be restored, the parameter R_{LA}, as shown in Fig. 1(a), is set at 9. The operation switches of $\underline{S}$ and $\overline{S}$ depicted in Fig. 1(b) are set at 3 and 17, respectively. In addition, the rated capacities ($\underline{D}$) for the feeder and lateral are 450A and 100A, respectively. However, in the daily operation of TPC, especially in the summer peak season, overloads of 10% and 20% for feeder and lateral, respectively, are allowed within a one hour period. Therefore, the parameter of $\overline{D}$ depicted in Fig. 1(c) for feeder and lateral is set at 495A and 120A, respectively. The same parameter for load balance objective is set. Further, the weighting values obtained by the AHP method [11] are 0.4673, 0.2772, 0.1601, and 0.0954 for *LR*, *SO*, *DO*, and *LB* objectives, respectively.

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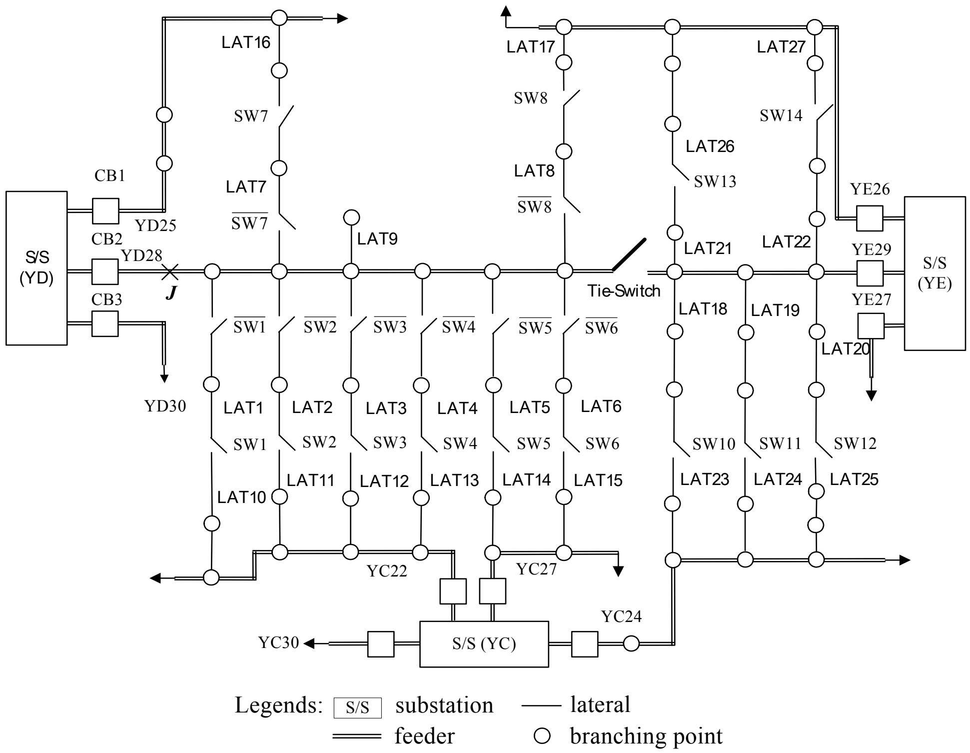

Fig. 2 A typical TPC 11-22kV distribution system.

5.2 Simulation Results of Different Cases

Table 1 shows the pre-fault data for lateral loads and feeders for different cases. These data are acquired for simulating the possible scenarios of the TPC distribution system. Fig. 3 depicts the optimization processes of the best fuzzy objective value obtained by the HBF, DE, and EDE methods. The figure reveals the proposed EDE converges more rapidly and achieves a higher fuzzy objective value than the other methods. After 9 iterations, the proposed EDE converges toward the best one while the DE and HBF methods require about 21 and 53 iterations, respectively. To verify the convergence performance of the proposed method, the simulations of convergence time through 100 trials with different random numbers are also executed. As shown in Table 2, the average convergence time obtained by the HBF, DE, and EDE methods are 11.25s, 6.10s, and 2.05s respectively.

Table 3 shows the best restoration schemes achieved by the proposed EDE and the other methods for different cases. The best fuzzy objective value and associated membership values obtained by each method are shown in Table 4. In case I, the proposed EDE and the other methods can restore all the lateral loads using an equal amount of operating switches. However, a slight overload took place on the supporting laterals of LTA15 (1A) by the HBF method. Compared to the DE method, the proposed EDE yields a better result from the view of load balance condition, as shown in Table 4.

As indicated in cases II and IV, the advantage of less operation switch is achieved by the proposed method while a slight overload takes place on the supporting feeder of YE29. In case III, the same restoration plan is obtained by the HBF and DE methods. The proposed EDE and the other methods can restore all the lateral loads using an equal amount of operating switches. However, no device overloads for the proposed method while slight overloads take place on the supporting laterals of LTA14 (3A) and LAT15 (2A) for the HBF and DE methods. Table 5 shows the obtained current on supporting laterals and feeders following restoration. The values with underline indicate they have been changed subsequent to restoration.

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Table 1 Pre-fault data for lateral loads and feeders for different cases.

Case I	Lateral	LAT1	LAT2	LAT3	LAT4	LAT5	LAT6	LAT7	LAT8	LAT9
	Ampere (A)	37	47	33	19	56	63	53	27	22
	Supporting Lateral	LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17	None
	Ampere (A)	51	39	46	37	34	38	23	80	
	Feeder	YD28	YD25	YC22	YC27	YE26	YE29			
	Ampere (A)	346	240	220	260	250	175			
Case II	Lateral	LAT1	LAT2	LAT3	LAT4	LAT5	LAT6	LAT7	LAT8	LAT9
	Ampere (A)	29	43	40	22	24	31	63	52	63
	Supporting Lateral	LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17	None
	Ampere (A)	74	56	61	63	78	69	35	47	
	Feeder	YD28	YD25	YC22	YC27	YE26	YE29			
	Ampere (A)	394	351	283	369	280	203			
Case III	Lateral	LAT1	LAT2	LAT3	LAT4	LAT5	LAT6	LAT7	LAT8	LAT9
	Ampere (A)	29	49	69	51	69	71	49	28	67
	Supporting Lateral	LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17	None
	Ampere (A)	51	39	24	37	34	31	60	80	
	Feeder	YD28	YD25	YC22	YC27	YE26	YE29			
	Ampere (A)	446	240	220	260	256	127			
Case IV	Lateral	LAT1	LAT2	LAT3	LAT4	LAT5	LAT6	LAT7	LAT8	LAT9
	Ampere (A)	35	45	31	17	54	61	51	25	20
	Supporting Lateral	LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17	None
	Ampere (A)	51	39	46	37	34	38	23	80	
	Feeder	YD28	YD25	YC22	YC27	YE26	YE29			
	Ampere (A)	346	240	220	260	250	175			

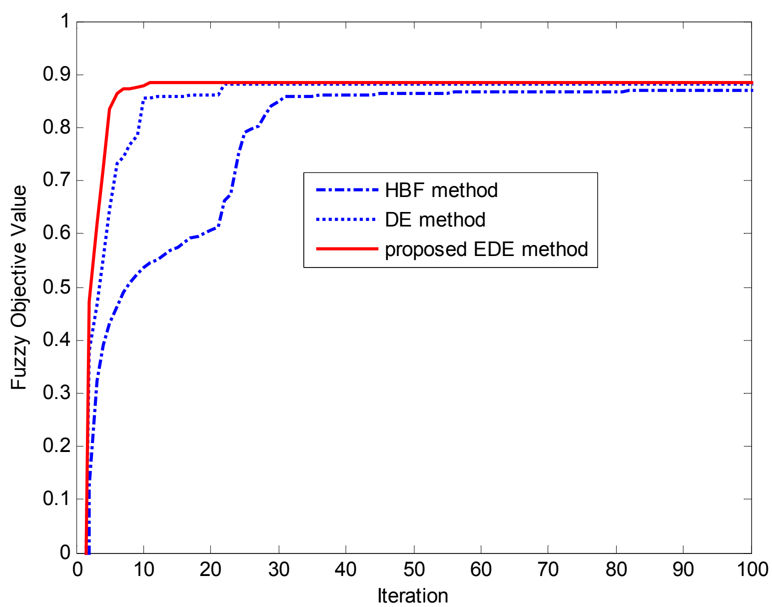

Fig. 3 Optimization of the best fuzzy objective value in population.

Table 2 Simulations of convergence time through 100 trials with different random numbers.

Methods	Ave.(s)	Min.(s)	Max.(s)	Max.-Min.(s)
HBF[1]	11.25	11.05	12.65	1.60
DE[2]	6.10	5.96	6.18	0.22
EDE[3]	2.05	2.03	2.13	0.10

[1]: Heuristic-based fuzzy method
[2]: Differential evolution method
[3]: Enhanced differential evolution method

Table 3 Best restoration plans reached by proposed EDE and other methods for different cases.

	Methods	Operated Switches	No. of Switches	Load Unrestored	Overload
Case I	HBF	Tie-Switch, SW6, $\overline{SW6}$, SW7, $\overline{SW7}$	5	None	LAT15(1A)
	DE	Tie-Switch, SW1, $\overline{SW1}$, SW3, $\overline{SW3}$	5	None	None
	EDE	Tie-Switch, SW5, $\overline{SW5}$, SW7, $\overline{SW7}$	5	None	None
Case II	HBF	Tie-Switch,SW5,$\overline{SW5}$, SW7,$\overline{SW7}$,SW8,$\overline{SW8}$	7	None	LAT14(2A)
	DE	Tie-Switch, W4,$\overline{SW4}$, SW7,$\overline{SW7}$,SW8,$\overline{SW8}$	7	None	None
	EDE	Tie-Switch,SW7,$\overline{SW7}$, SW8,$\overline{SW8}$	5	None	YE29(5A)
Case III	HBF	Tie-Switch,SW2,$\overline{SW2}$, SW5,$\overline{SW2}$,SW6,$\overline{SW6}$	7	None	LAT14(3A) LAT15(2A)
	DE	Tie-Switch,SW2,$\overline{SW2}$, SW5,$\overline{SW2}$,SW6,$\overline{SW6}$	7	None	LAT14(3A) LAT15(2A)
	EDE	Tie-Switch,SW2,$\overline{SW2}$, SW3,$\overline{SW3}$,SW4,$\overline{SW4}$	7	None	None
Case IV	HBF	Tie-Switch,SW5,$\overline{SW5}$, SW7,$\overline{SW7}$	5	None	None
	DE	Tie-Switch,SW6,$\overline{SW6}$, SW7,$\overline{SW7}$	5	None	None
	EDE	Tie-Switch, SW6,$\overline{SW6}$	3	None	YE29(3A)

Table 4 Best fuzzy objective value and the associated membership functions for different cases.

	Methods	*LR*[1]	*SO*[2]	*DO*[3]	*LB*[4]	Best Fuzzy Objective Value
Case I	HBF	1.0000	0.8571	0.9500	0.2317	0.8791
	DE	1.0000	0.8571	1.0000	0.1906	0.8832
	EDE	1.0000	0.8571	1.0000	0.2250	0.8865
Case II	HBF	1.0000	0.7143	0.9000	0.2000	0.8285
	DE	1.0000	0.7143	1.0000	0.1938	0.8439
	EDE	1.0000	0.8571	0.8889	0.1370	0.8603
Case III	HBF	1.0000	0.7143	0.8500	0.1977	0.8202
	DE	1.0000	0.7143	0.8500	0.1977	0.8202
	EDE	1.0000	0.7143	1.0000	0.1688	0.8415
Case IV	HBF	1.0000	0.8571	1.0000	0.2688	0.8903
	DE	1.0000	0.8571	1.0000	0.2561	0.8889
	EDE	1.0000	1.0000	0.9333	0.1313	0.8932

[1]Load restoration, [2]: Switches operation, [3]Devices overload, [4]Load balance

Table 5 Current (A) on supporting laterals and feeders following restoration for different cases.

	Methods	LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17
Case I	HBF	51	39	46	37	34	101	76	80
	DE	88	39	79	37	34	38	23	80
	EDE	51	39	46	37	90	38	76	80
		YD25	YC22	YC27	YE26	YE29			
	HBF	293	220	316	250	416			
	DE	240	290	260	250	434			
	EDE	293	220	316	250	423			
Case II		LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17
	HBF	74	56	61	63	102	69	98	99
	DE	74	56	61	85	78	69	98	99
	EDE	74	56	61	63	78	69	98	99
		YD25	YC22	YC27	YE26	YE29			
	HBF	414	283	393	332	431			
	DE	414	305	369	332	433			
	EDE	414	283	369	332	455			
Case III		LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17
	HBF	51	88	24	37	103	102	60	80
	DE	51	88	24	37	103	102	60	80
	EDE	51	88	93	88	34	31	60	80
		YD25	YC22	YC27	YE26	YE29			
	HBF	240	269	400	256	421			
	DE	240	269	400	256	421			
	EDE	240	389	260	256	441			
Case IV		LAT10	LAT11	LAT12	LAT13	LAT14	LAT15	LAT16	LAT17
	HBF	51	39	46	37	34	99	74	80
	DE	51	39	46	37	88	38	74	80
	EDE	51	39	46	37	34	99	23	80
		YD25	YC22	YC27	YE26	YE29			
	HBF	291	220	314	250	409			
	DE	291	220	321	250	402			
	EDE	240	220	321	250	453			

5.3 Discussions

According to the results, some observations are summarized as follows.

(1) As shown in cases II and IV, the proposed approach achieves the better restoration plan with less operation switch. It is significant that even when the distribution automation project in TPC is completed, only the feeder loads will be monitored and operated by remote control. The switches on laterals will be operated manually by the system operators. Therefore, the restoration plan with less operation switches can save more restoration time.

(2) Cases II and IV also show the proposed method achieves a better restoration plan with a slight overload on the supporting feeder of YE29. It is allowable for TPC within a one hour period, especially in the summer peak season.

(3) Due to the contribution of VSDE and AS algorithms, the proposed EDE converges more rapidly and achieves a higher fuzzy objective value than the other methods. It reveals the proposed EDE can provide a better restoration plan with less restoration time and a more satisfactory solution to the operators.

6. Conclusions

In this paper, a new combinatorial optimization approach using the EDE algorithm was developed for rapidly restoration of distribution systems. The proposed EDE combines the VSDE and AS methods to enhance the capability of global search in the population. Following an efficient algorithm, the final best restoration plan is then attained. Testing on different cases for a typical TPC 11-22kV distribution system revealed the results derived from the EDE approach coincided with the results from the practical operators. The proposed EDE method can reach the best restoration play very quickly and has a better performance than the HBF and classical DE methods. Although this paper only dealt with a fault occurring at one specific location, the proposed approach is also suitable to deal with faults occurring at any other locations.

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