Comprehensive Cost Minimization in Distribution Networks Using Segmented-Time Feeder Reconfiguration and Reactive Power Control of Distributed Generators

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***Abstract*—In this paper, an efficient methodology is proposed to deal with segmented-time reconfiguration problem of distribution networks coupled with segmented-time reactive power control of distributed generators. The target is to find the optimal dispatching schedule of all controllable switches and distributed generators' reactive powers in order to minimize comprehensive cost. Corresponding constraints, including voltage profile, maximum allowable daily switching operation numbers (MADSON), reactive power limits, and so on, are considered. The strategy of grouping branches is used to simplify the formulated mathematical problem and a hybrid particle swarm optimization (HPSO) method is presented to search the optimal solution. Fuzzy adaptive inference is integrated into basic HPSO method in order to avoid being trapped in local optima. The proposed fuzzy adaptive inference-based hybrid PSO algorithm (FAHPSO) is implemented in VC++ 6.0 program language. A modified version of the typical 70-node distribution network and several real distribution networks are used to test the performance of the proposed method. Numerical results show that the proposed methodology is an efficient method for comprehensive cost minimization in distribution systems with distributed generators.**

***Index Terms*—Distributed generator, fuzzy adaptive inference, hybrid particle swarm optimization (HPSO), segmented-time reactive power control, segmented-time reconfiguration.**

I. Introduction

DISTRIBUTION network reconfiguration (DNR) is very useful to the optimal operation of electric distribution systems [1]–[3]. By regulating the topology structure of distribution networks, electric power companies can provide better electric power and gain more profits. The corresponding formulation is a mixed-integer nonlinear programming (MINLP) problem. At the same time, many distributed generators are connected into distribution networks today. Distributed generators can also provide reactive power to distribution networks to improve the operation of distribution network as ancillary contributions when they supply uncertain active powers to power grids. Hence, it is very significant to couple distribution network reconfiguration with reactive power control of distributed generators. Because of the hourly load forecast and active power forecast of distributed generators, both distribution network reconfiguration and reactive power control of distributed generators need to be done in the segmented-time mode. In order to do this, the dispatching schedule of next day should be calculated in advance. As a result, the corresponding MINLP problem becomes more complex. Moreover, as the number of the controllable switches and distributed generators increases, it may be curse of dimensionality.

In recent years, considerable researches on distribution network reconfiguration were done. In [2], Benders Decomposition Technique is used to solve the reconfiguration problem coupled with optimal power flow. The main problem and the slave problem are solved by the solvers CPLEX and CONOPT, respectively. In [4], Young-Jae Jeon, *et al.* proposed an efficient simulated annealing algorithm to solve the reconfiguration problem of distribution networks. They improved the perturbation mechanism with system topology and used the polynomial-time cooling schedule. However, in [2] and [4], neither load uncertainties nor active power uncertainties of distributed generators were dealt with. In [5] and [6], differential evolution methods were used to solve the same problem and the variable scaling factor overcame the drawback of the fixed and random scaling factor. In [7] and [8], improved ant colony optimization methods were proposed to deal with the same problem. Ashish Ahuja *et al.* proposed a hybrid algorithm based on artificial immune systems and ant colony optimization for distribution networks. As a result, the search space was explored by means of the hypermutation operator quickly. However, reactive powers of distributed generators were not used to enhance the operation of distribution networks together with distribution system reconfigurations in their researches. In [9], Srinivasa Rao *et al.* used harmony search algorithm to solve the reconfiguration problem of distribution network in order to get the optimal switching combination. In [10], the authors further investigated how to utilize reactive powers of

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distributed generators to enhance the operation of distribution networks as ancillary services. However, load uncertainties were not dealt with in their researches. In [11]–[13], a genetic algorithm was used to search the optimal switching combination and a few variants of genetic methods were proposed. In these methods, new coding strategies, including node-depth encoding, sequential encoding, Matriod theory-based encoding, and so on, were adopted. Genetic algorithm can improve the quality of the global solution, but it is time consuming. In [14] and [15], evolutionary algorithms were used to search the optimal solution. In [16]–[19], particle swarm optimization (PSO) methods were used to solve the same problem. Load uncertainties and active power uncertainties of distributed generators were dealt with from the perspective of electric power market in [18]. In [20]–[22], integer-coding-based PSO methods were proposed to simplify the formulation of the MINLP problem in order to accelerate the searching process. In [23]–[25], fuzzy adaptive inference was used to enhance the performance of PSO algorithm with its non-linear and dynamic characteristic. However, it is obvious that all of the methods cannot be directly used to deal with the segmented-time reconfiguration problem of distribution networks coupled with the optimal reactive power control of distributed generators.

In this paper, segmented-time reconfiguration problem of distribution networks, coupled with segmented-time reactive power control of distributed generators, is investigated. The optimization objective is to minimize comprehensive operation costs of distribution networks. The key contributions of this paper are summarized as follows. First, the formulation of segmented-time reconfiguration problem for distribution networks coupled with segmented-time reactive power control of distributed generators is proposed. The effects of distributed generators and other various constraints are considered in the formulation. Second, the strategy of grouping branches is adopted in order to reduce the complexity of the proposed formulation. The computation burden is mitigated by using the proposed strategy. Third, a hybrid PSO algorithm is proposed to solve the formulated MINLP problem and fuzzy adaptive inference logic is used to improve the iteration process. With the proposed FAHPSO method, the problem of being trapped in local optima is effectively avoided.

The remainder of this paper is structured as follows. Section II describes the formulation of the MINLP problem. Section III presents the basic HPSO method and the fuzzy adaptive inference based HPSO method. Numerical experiments are finished in Section IV. Section V summarizes the contributions of this paper.

II. Problem Formulation

Normally, the target of reconfiguring distribution networks is to minimize power loss. In segmented-time distribution network reconfiguration (SDNR), each switch is operated many times in one day and each operation associates with some operation cost. Hence, it is significant to choose comprehensive cost minimization as the objective function. Comprehensive cost consists of power loss cost and operation cost of switches and it is calculated by

$$F = K_l P_{\text{Loss}} + K_s A_s \tag{1}$$

where P_{Loss} is the active power loss of the studied distribution network (kwh), K_l is the electricity price per kilowatt-hour, A_s is the total operation number of all controllable switches, K_s is the cost of one ON/OFF switching operation.

According to forecast segmented-time load curve and active power curve of distributed generators, the whole control scheme of all switches and all distributed generators should be calculated in advance. During each small segment, a concrete control decision is executed. Here, forecast load curves and active power curves of distributed generators are all assumed to be divided into N_L small segments. Hence, the total decision is presented as

$$X = [X_1, X_2, \cdots, X_t, \cdots, X_{N_L}]\,. \tag{2}$$

Each X_t can be further presented as

$$X_t = [S_t, Q_t] \tag{3}$$

where S_t and Q_t are the status vector of all controllable switches and the reactive power vector of all controllable distributed generators during time segment t, respectively. Suppose that the number of all controllable switches is N_s and the number of all controllable distributed generators is N_{g}, then S_t and Q_t are further represented as

$$S_t = [s_{t,1}, s_{t,2}, \cdots, s_{t,N_S}] \tag{4}$$

$$Q_t = [q_{t,1}, q_{t,2}, \cdots, q_{t,N_{\text{g}}}]\,. \tag{5}$$

From (2)–(5), we can see that the dimension number of X is $N_L \cdot (N_s + N_{\text{g}})$.

According to the settings of S_t and Q_t, the power flow calculation during time segment t is finished by the back/forward sweep method. Then, the power loss of the studied distribution network during time segment t is calculated by

$$P_{Loss.t} = \Delta T_t \sum_{i=1}^{N_b} \left(I_{i.t}^2 \cdot R_i\right) \tag{6}$$

where N_b is the branch number of the whole system, ΔT_t is the length of time segment t, R_i is the resistance of branch i, and $I_{i.t}$ is the current of branch i corresponding to time segment t.

With the same procedures, the power flow computations of all time segments are finished and the total power loss P_{Loss} in (1) is presented as

$$P_{\text{Loss}} = \sum_{t=1}^{N_L} P_{\text{Loss.t}} = \sum_{t=1}^{N_L} \Delta T_t \sum_{i=1}^{N_b} \left(I_{i.t}^2 \cdot R_i\right). \tag{7}$$

On the other hand, the operation number of switch n in one day is calculated by

$$A_{s.n} = \sum_{t=1}^{N_L} \left| s_{n.t} - s_{n.(t-1)} \right| \tag{8}$$

where $s_{n.t}$ is the status value of switch n corresponding to time segment t. If this switch is on, $s_{n.t}$ equals to 1; otherwise, if this switch is off, $s_{n.t}$ equals 0. $s_{n.0}$ is the ending status of switch n in the previous day.

Further, the total operation number of all switches A_s in (1) is calculated by

$$A_s = \sum_{n=1}^{N_s} A_{s.n} = \sum_{n=1}^{N_s}\sum_{t=1}^{N_L} \left| s_{n.t} - s_{n.(t-1)} \right|. \tag{9}$$

From (1), (7) and (9), the objective function is presented as

$$\begin{aligned} \text{Min } F = & K_l \sum_{t=1}^{N_L} \Delta T_t \sum_{i=1}^{N_b} \left(I_{i.t}^2 \cdot R_i \right) \\ & + K_s \sum_{n=1}^{N_s}\sum_{t=1}^{N_L} \left| s_{n.t} - s_{n.(t-1)} \right| \end{aligned} \tag{10}$$

At the same time, the corresponding constraints are summarized as follows.

1) *Radial network constraint*:

$$\sum_{l=1}^{N_b} \alpha_l = N_{\text{Load}} \tag{11}$$

$$\beta_{ij} + \beta_{ji} = \alpha_l, \quad l = 1, \cdots, N_b \tag{12}$$

$$\sum_{j \in N(i)} \beta_{ij} = 1, \quad i = 1, \cdots, N_{\text{Load}} \tag{13}$$

$$\sum_{f \in R(k)} \beta_{kf} = 0, \quad k = 1, \cdots, N_{\text{Root}} \tag{14}$$

$$\beta_{ij} \in \{0, 1\}, \quad i = 1, \cdots, N_{\text{Load}}, \quad j \in N(i). \tag{15}$$

In (11) and (12), α_l is a binary variable and it indicates the status of line l. α_l equals to 1 when line l is connected to a radial distribution network. $\alpha_l = 0$ means that line l is not connected to any radial distribution network. In (12), (13) and (15), β_{ij} and β_{ji} are two binary variables, respectively. β_{ij} is set to 1 if node j is the parent of node i whereas β_{ji} is set to 1 if node i is the parent of node j. In (12), node i and node j are the terminals of line l. In (13) and (14), N_{Load} and N_{Root} are the numbers of load nodes and root nodes, respectively. $N(i)$ is the set of nodes connected to load node i by a line and $R(k)$ is the set of nodes connected to root node k by a line. In (14), β_{kf} is used to indicate if node f is the parent of root node k. Equation (11) guarantees that all load nodes are connected to radial distribution networks, (13) indicates that each load node has only one parent and (14) indicates that each root node has no parent. Constraints (11)–(15) guarantee together that the concerned networks are radial and all load nodes are energized.

2) *Active power balance constraint*:

$$\sum_{j \in N(i)} V_{i.t} V_{j.t} (G_{ij.t} \cos\theta_{ij.t} + B_{ij.t} \sin\theta_{ij.t})] = P_{DG.i.t} - P_{D.i.t} \tag{16}$$

where $N(i)$ is the subset of the adjacent nodes connected to node i by the corresponding lines, $\theta_{ij.t}$ is the voltage angle difference between node i and node j during time segment t, namely, $(\theta_{i.t} - \theta_{j.t})$, $G_{ij.t}$ is the real term of the element i, j in node admittance matrix during time segment t, $B_{ij.t}$ is the imaginary term of the element i, j in node admittance matrix during time segment t, $P_{DG.i.t}$ is the active power injected by the generating unit at node i during time segment t, $P_{D.i.t}$ is the active load demand at node i during time segment t. $V_{i.t}$ and $V_{j.t}$ are the voltage amplitudes of node i and node j during time segment t, respectively.

3) *Reactive power balance constraint*:

$$\sum_{n \in N} V_{i.t} V_{j.t} (G_{ij.t} \sin\theta_{ij.t} - B_{ij.t} \cos\theta_{ij.t})] = Q_{DG.i.t} - Q_{D.i.t} \tag{17}$$

where $Q_{DG.i.t}$ is the reactive power injected by the generating unit connected at node i and $Q_{D.i.t}$ the reactive load demand at node i during time segment t.

4) *Maximum Daily allowable switching operation number constraint*:

$$A_{s.n} \leq A_{Max.s.n}, \quad n \in (1, N_s) \tag{18}$$

where $A_{Max.s.n}$ is the maximum allowable daily switching operation number (MADSON) of switch n. $A_{s.n}$ is calculated in (8).

5) *Voltage limit constraint*:

$$V_{\text{Min}} < \underset{i \in (1 \sim N_b), t \in (1 \sim N_L)}{V_{i.t}} < V_{\text{Max}} \tag{19}$$

where V_{Min} is the lower voltage limit and V_{Max} is the upper voltage limit and $V_{i.t}$ is the voltage amplitude of node i during time segment t.

6) *Current limit (Or heat limit) constraint*:

$$\underset{b \in (1 \sim N_b), t \in (1 \sim N_L)}{I_{b.t}} < I_{\text{Max.b}} \tag{20}$$

where $I_{\text{Max.b}}$ is the current limit of branch b and $I_{b.t}$ is the current of branch b corresponding to time segment t.

7) *Capacity limit constraint of reactive power of distributed generator*:

$$q_{\text{Min.g.}t} < \underset{g \in (1, N_{\text{g}})}{q_{\text{g.}t}} < q_{\text{Max.g.}t} \tag{21}$$

where $q_{\text{g.}t}$, $q_{Min\text{.g.}t}$, and $q_{Max\text{.g.}t}$ are the control output, the lower limit, and the upper limit of the reactive power of distributed generator g during time segment t, respectively. $q_{\text{Min.g.}t}$ and $q_{\text{Max.g.}t}$ are subject to different physical/hardware constraints of different DGs. In this paper, $q_{\text{Min.g.}t}$ and $q_{\text{Max.g.}t}$ are calculated with the characteristic equation of doubly fed induction generator (DFIG)-based wind turbines [26].

III. Proposed Method

In the past 20 years, many artificial intelligent methods were proposed to deal with the problem of distribution network reconfiguration, such as the simulated annealing method (SA) [4], differential evolution method (DE) [5], [6], ant colony optimization algorithm (ACO) [7], [8], harmony search algorithm (HSA) [9], [10], genetic algorithm (GA) [11]–[13], evolutionary algorithm (EA) [14], [15], particle swarm optimization method

(PSO) [16]–[22], and so on. Among them, PSO has many good performances, including good robustness and fast convergence. In this paper, PSO is used to solve the aforementioned MINLP problem.

A. Overview of PSO

PSO algorithm is an evolutionary method which considers the behavior of bird flocking or fish schooling. In this method, each potential solution is presented as a particle and each particle corresponds to a fitness index, which is calculated by the fitness function. In the evolution process, each particle has its own speed to regulate its flying direction. The basic PSO method is presented as

$$\begin{cases} v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(g_{id}^{k} - x_{id}^{k}\right) \\ x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \end{cases} \tag{22}$$

where both c_1 and c_2 are nonnegative constant coefficients called as leaning factors. Both r_1 and r_2 are random float numbers, varying in range [0, 1]. v_{id}^{k} is the speed of particle i during cycle k and x_{id}^{k} is the position of particle i during cycle k. At the same time, p_{id}^{k} is the best personal position of particle i until cycle k and g_{id}^{k} is the best global position among all particles until cycle k. w is the inertia constant coefficient.

B. Strategy of Grouping Branches and Particle Model

As the ON/OFF status of each switch corresponds to a binary variable, each switch status is regarded naturally as a particle dimension. As a result, the total particle dimension number is $N_L \cdot (N_s + N_{\mathrm{g}})$ As the switch number increases, it may be curse of dimensionality. Here, a strategy is presented to group branches in order to reduce the dimension number. In the presented grouping strategy, the branches of the same group are subject to the following rules.

1) All branches lie in a continuous feeder section.
2) The starting node of the feeder section corresponding to each branch group is a root node or a junction node.
3) The ending point of the feeder section corresponding to each branch group is also a junction node (or a root node).
4) Except the starting node and the ending node, there are no other junction nodes or (root nodes) within the given continuous feeder section.

The presented strategy of grouping branches is demonstrated in Fig. 1.

In Fig. 1, nodes 5, 7, and 11 are three junction nodes, respectively, and nodes 0, 3, 8, 12, and 16 are five root nodes (source nodes), respectively. S0, S1, $\cdots$, and S10 are eleven sectionalizing switches. T11, T12, $\cdots$, and T15 are five tie-switches. In accordance with the rules of grouping branches, the distribution network is divided into seven branch groups. Each dashed-line region is a branch group. In a real distribution network, merely one switch is permitted to be switched off at most within each branch group. The target is to guarantee that all nodes are energized. Suppose that there are N_i branches in branch group i all branches are numbered from 1 to N_i. Here, an integer y_i is used to represent the sequence number of the OFF branch of group i When y_i equals to 0, it means that all branches in branch group i are ON, namely, no branch is off. As a result, the corresponding

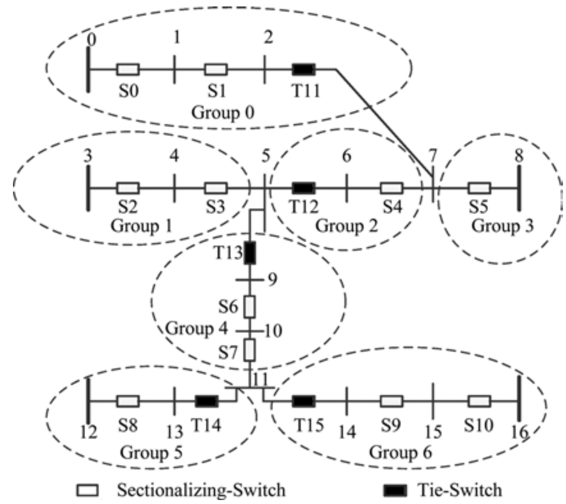

Fig. 1. Strategy of grouping branches.

status variable of each branch group is an integer. Hence, the particle model of distribution network reconfiguration coupled with reactive power control of distributed generators is represented in a new way as given by

$$P = [P_1, P_2, \cdots, P_t, \cdots, P_{N_L}]. \tag{23}$$

In (23), each P_t in P is a set of N_G branch sequence numbers and N_{g} reactive power outputs of distributed generators. P_t is further represented as

$$P_t = \left[g_{t.1}, g_{t.2}, \cdots, g_{t.N_G}, q_{t.1}, q_{t.2}, \cdots, q_{t.N_{\mathrm{g}}}\right]. \tag{24}$$

According to (23) and (24), the dimension number of P is presented as $N_L \cdot (N_G + N_{\mathrm{g}})$. Since N_G is much less than N_s, the dimension number is greatly reduced, which accelerates the procedure of searching the optimal solution. A transfer from P to X is necessary in order to realize topology analysis and power flow calculation. As the transfer procedure is simple, it is omitted here.

C. Basic Hybrid PSO Algorithm

In (23), the value types of particle positions include integers and float numbers. Given the diversity of position values, a hybrid PSO algorithm is proposed to deal with the MINLP problem.

As for the sequence number of the OFF branch of each group, it is an integer and varies in the range $[0, \mathrm{g}_{Max.i}]$. $\mathrm{g}_{Max.i}$ is the maximum sequence number (branch number) of branch group i. Hence, the integer PSO algorithm is used to deal with the evolution of the sequence number of the OFF branch as follows:

$$v_{id}^{k+1} = wv_{id}^{k} + r_1 \cdot c_1. \left(p_{id}^{k} - x_{id}^{k}\right) + r_2 \cdot c_2. \left(\mathrm{g}_{id}^{k} - x_{id}^{k}\right) \tag{25}$$

$$x_{I.id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{26}$$

$$x_{II.id}^{k+1} = \mathrm{round}\left(x_{I.id}^{k+1}\right) \tag{27}$$

$$x_{id}^{k+1} = \begin{cases} 0, & x_{II.id}^{k+1} < 0 \\ x_{II.id}^{k+1}, & 0 \le x_{II.id}^{k+1} \le \mathrm{g_{Max.i}} \\ \mathrm{g_{Max.i}}, & x_{II.id}^{k+1} > \mathrm{g}_{Max.i} \end{cases} \tag{28}$$

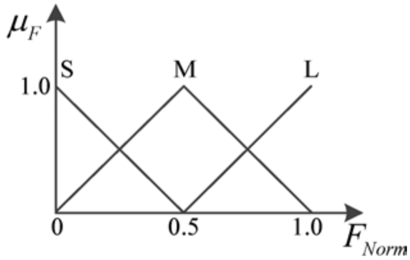

Fig. 2. Membership of the normalized comprehensive cost in the fuzzy system.

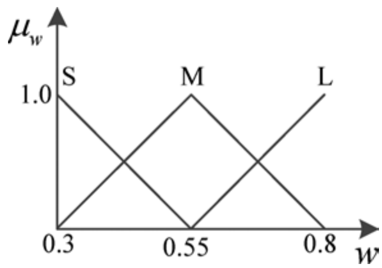

Fig. 3. Membership of the inertia weight in the fuzzy system.

where the function $round(\cdot)$ is used to calculate the expected integer based on rounding rule.

As the reactive power outputs of distributed generators are floating numbers and vary in the range $[q_{\mathrm{Min.i},q_{\mathrm{Max.i}}}]$, the continuous PSO method is used to deal with the reactive power outputs of distributed generators

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(\mathrm{g}_{id}^{k} - x_{id}^{k}\right) \tag{29}$$

$$y_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{30}$$

$$x_{id}^{k+1} = \begin{cases} q_{\mathrm{Min.i}}, & y_{id}^{k+1} < q_{\mathrm{Min.i}} \\ y_{id}^{k+1}, & q_{Min.i} \le y_{id}^{k+1} \le q_{Max.i} \\ q_{\mathrm{Max.i}}, & y_{id}^{k+1} > q_{\mathrm{Max.i}} \end{cases} \tag{31}$$

where $q_{\mathrm{Min.i}}$ and $q_{\mathrm{Max.i}}$ are the lower limit and the upper limit of the reactive power output of the corresponding distributed generator during the corresponding time segment, respectively.

D. Improvement of Basic Hybrid PSO Algorithm Using Fuzzy Adaptive Inference

The basic hybrid PSO algorithm usually suffers from the problem of being trapped in local optima and it is time-consuming. Good dynamic balance between global and local search abilities is useful to avoid being trapped in local optima and enhance the efficiency of the aforementioned hybrid PSO algorithm [25]. According to the literatures [24], [25], fuzzy adaptive system has nonlinear and dynamic performance. Hence, it may be used to tune the inertia weight of the basic hybrid PSO method in order to realize better dynamic performance. In this paper, fuzzy adaptive inference is used to improve the dynamic performance of the inertia weight in order to avoid the premature problem and improve the performance of basic hybrid PSO algorithm.

A fuzzy system includes three important steps, namely, fuzzification, fuzzy logic inference and defuzzification. First, it maps sets of input variables into fuzzy sets using membership functions. Second, according to the predefined logic rules, the output

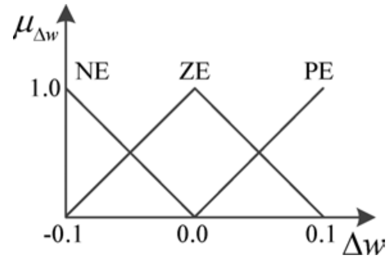

Fig. 4. Membership of the inertia weight deviation in the fuzzy system.

is assigned based on these fuzzy input sets. Third, according to fuzzy value outputs and their membership, the true output is calculated. In this paper, input variables include the normalized comprehensive cost of the best particle up to the newest iteration and the current inertia weight of each particle. Output variable is the inertia weight deviation. The result of fuzzy logic inference is some fuzzy values and their membership values.

Since the real comprehensive cost normally exceeds the range $[0 \sim 1.0]$, it needs to be normalized. The normalized comprehensive cost is defined as

$$F_{\mathrm{Norm}} = \frac{F_{\mathrm{Cur}} - F_{\mathrm{Min}}}{F_{\mathrm{Max}} - F_{\mathrm{Min}}} \tag{32}$$

where F_{Cur} is current real comprehensive cost in each iteration calculated by (1). F_{Max} is a large value which is greater than or equals to any feasible comprehensive cost. F_{Min} is a small value which is less than or equals to any feasible comprehensive cost. The value of inertia weight is limited in the range $[0.3 \sim 0.8]$. In reference [27], 0.8 is regarded as the best inertia weight. The deviation of inertia weight is limited in the range $[-0.1 \sim 0.1]$. The input fuzzy variables are defined in three fuzzy sets of linguistic values S (small), M (medium) and L (large) with the associated membership functions, as shown in Fig. 2 and Fig. 3, respectively.

The output variable is presented in three fuzzy sets of linguistic values NE (negative), ZE (zero) and PE (positive) with associated membership functions, as shown in Fig. 4.

In order to calculate the inertia deviation Δw, a fuzzy inference logic, which consists of nine rules, is shown in Table I. In Table I, there are nine possible rules for the two input variables since each input variable has three linguistic values. The Larsen product has been used as the fuzzy implication operator for the individual rules. Firing of each rule separately results in clipped output fuzzy sets, one for each rule. The overall fuzzy output is being obtained by combining all the clipped fuzzy sets. The aggregated fuzzy output is converted into a single value using centroid defuzzification method.

Once the deviation of the inertia weight Δw^k during evolution step k is calculated, the new inertia weight w^{k+1} of iteration $k+1$ can be updated as follows.

$$w^{k+1} = w^k + \Delta w^k \tag{33}$$

The above fuzzy adaptive inference of inertia weight is integrated to the basic hybrid PSO algorithm. As a result, the proposed fuzzy adaptive inference-based hybrid particle swarm optimization (FAHPSO) algorithm is shown in Fig. 5.

TABLE I
FUZZY RULES FOR THE INERTIA WEIGHT DEVIATION

Rule no	Antecedent		Consequent
	F_{Norm}	w	Δw
1	*S*	*S*	ZE
2	*S*	*M*	NE
3	*S*	*L*	NE
4	*M*	*S*	PE
5	*M*	*M*	ZE
6	*M*	*L*	NE
7	*L*	*S*	PE
8	*L*	*M*	ZE
9	*L*	*L*	NE

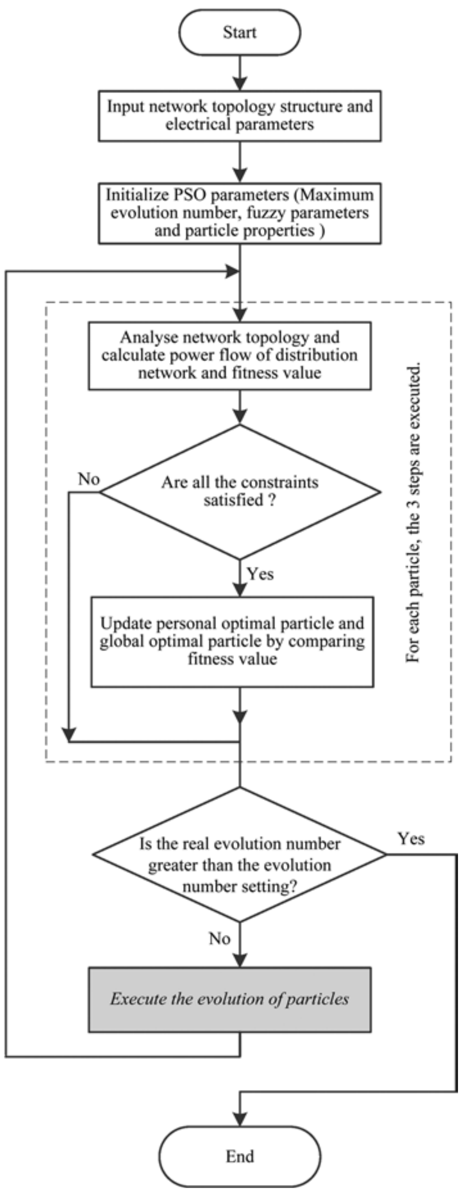

Fig. 5. Flowchart of FAHPSO.

In Fig. 5, the fuzzy adaptive inference process is integrated in the "*Execute the evolution of particles*" module. By this module, all of the particles are updated. In the dashed rectangle, the fitness indices of all particles are calculated and compared with their own current optimal indices and current global optimal index, respectively. By comparisons, all optimal particles and global optimal particles are updated.

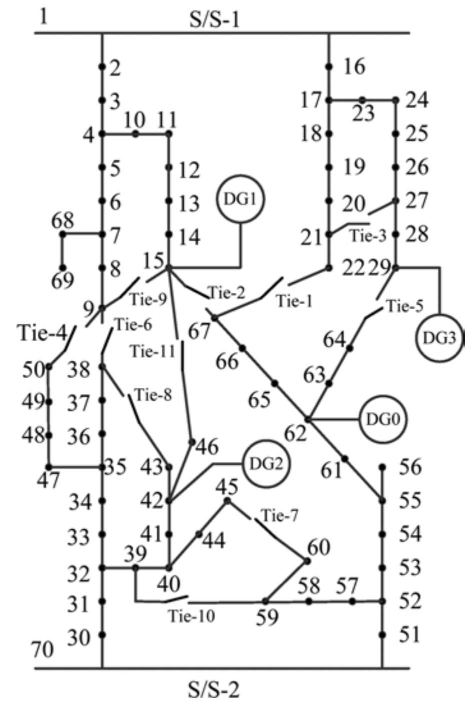

Fig. 6. Modified version of the 70-node distribution system.

IV. NUMERICAL EXPERIMENTS

A. Test Case Network

In order to test the performance of the proposed FAHPSO algorithm, VC++ 6.0 program language is used to develop the corresponding software system. By the developed software system, the proposed FAHPSO algorithm and other methods are implemented. The developed software system runs on a PC computer with Windows 7 operation system. Here, a modified version of the distribution network used in [23], which is shown in Fig. 6, is used to test the proposed FAHPSO algorithm.

In the initial distribution network, there are two substations, four feeders, 70 nodes, and 78 branches (including tie branches). Four distributed generators are newly added to this distribution network. They are installed at nodes 15, 29, 42, and 62, respectively. The rated active power of each distributed generator is 400 kw.

In order to emulate load uncertainties and limit the complexity of the studied problem, all the loads are divided into three groups. Group one includes Load 0, Load 3, Load 6, $\cdots$, Load 66, and Load 69. Group two includes Load 1, Load 4, Load 7, Load 10, $\cdots$, Load 67, and Load 70. Group three includes Load 2, Load 5, Load 8, $\cdots$, Load 65, and Load 68. Each group has its own load curve and all the loads in the same group have the same normalized load curve. Three normalized load curves are shown in Fig. 7, respectively.

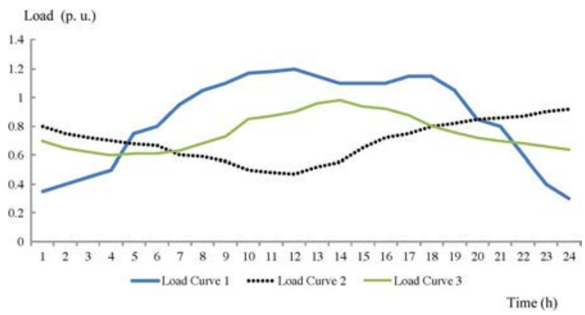

Fig. 7. Three normalized load curves.

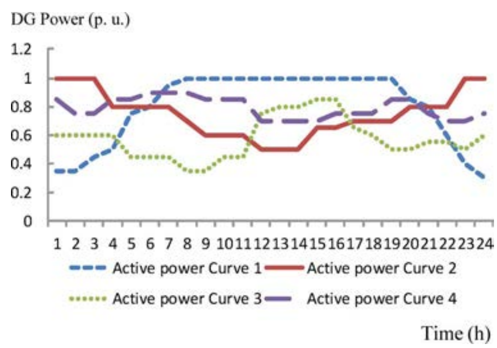

Fig. 8. Four normalized curves of DG active powers.

At the same time, in order to emulate active power uncertainties of distributed generators, four different normalized active power curves are used to represent the uncertainties of DG0, DG1, DG2, and DG3 as shown in Fig. 8.

Based on the load forecast curves shown in Fig. 8, eight corresponding reactive power limit curves of four distributed generators are calculated. The calculated reactive power limit curves are used to limit the ranges of the reactive power outputs of four distributed generators corresponding to 24 time segments of the future day, respectively.

The procedure of grouping branches is finished and the whole distribution network is divided into 28 branch groups. Three branches, namely branch 7–68, branch 68–69, and branch 55–56, cannot be assigned to any branch group since they should keep ON all the time in order to guarantee that the corresponding nodes are energized. The voltage setting of root nodes is 12 kV, K_l is 0.4, K_s is 0.5 and the maximum allowable daily switching operation number is 16. These parameters are from Chengdu Power Supply Bureau of China. The particle number is 30 and the iteration cycle number is 200. c_1 and c_2 are both 2.0. The lower and upper limits of particle velocities are -4.0 and 4.0, respectively. These settings are selected from [27].

B. Test of the Rationality of Using Comprehensive Cost as the Optimization Objective

In order to verify the rationality of using comprehensive cost as the optimization objective, two scenarios are chosen to calculate the optimal reconfiguration scheme. They are the scenario of minimizing power loss (Scenario A) and the scenario of minimizing comprehensive cost (Scenario B), respectively. Under the chosen scenarios, the basic hybrid PSO method is used to solve the MINLP problem. In the experiment, only network reconfiguration is permitted. The corresponding iteration curves are shown in Fig. 9.

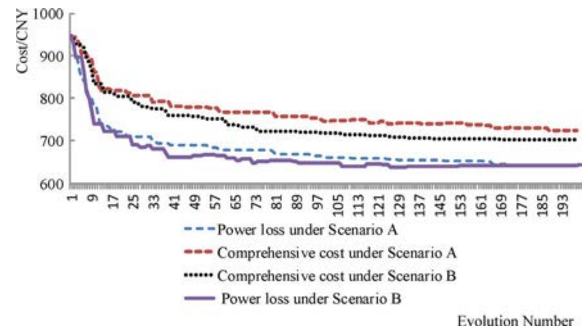

Fig. 9. Iteration curves under different objectives.

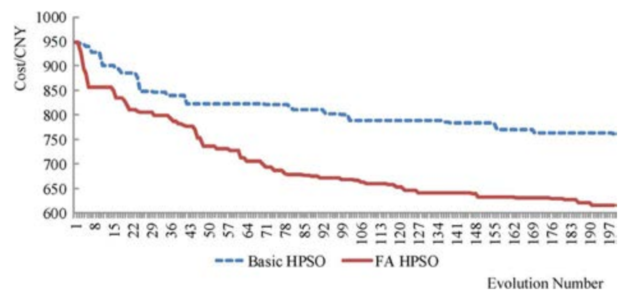

Fig. 10. Performance test of fuzzy adaptive inference.

Four curves are shown in Fig. 9. Two of them are produced under Scenario A and the other two are produced under Scenario B. These curves show the iteration processes of power losses and comprehensive costs, respectively. By the comparisons, it is verified that the final comprehensive cost under Scenario B is less than the comprehensive cost under Scenario A in despite of the fact that the final power losses of two scenarios are almost equal. From Fig. 9, it can be seen that 2.8% of the total cost is saved since the comprehensive cost is selected as the objective function.

C. Performance Test of Fuzzy Adaptive Inference

In order to verify the performance of the fuzzy adaptive inference to improve the efficiency and convergence of the basic hybrid PSO method, both the basic hybrid PSO method and the improved FAHPSO are used to search the schedule of switches and reactive powers of distributed generators. In the test, the optimization objective is to minimize the comprehensive cost. The calculation processes are shown in Fig. 10.

At the same time, the corresponding optimal results are shown in Table II.

According to Fig. 10 and Table II, FAHPSO can find better schedule for the studied distribution network within the limited iteration cycles, compared with basic HPSO method. It can be seen that FAHPSO has good convergence and dynamic performance and it can escape local optima, effectively.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE II
CALCULATION RESULT COMPARISON BETWEEN BASIC HPSO AND FAHPSO

Indices \ Methods	HPSO	FAHPSO
Comprehensive Cost (CNY)	762	614
Network Loss(CNY)	585	534
Switch Operation Number	354	160
Consumed Time(Second)	320	310
Cycle Number of Reaching Stable Solution	169	191

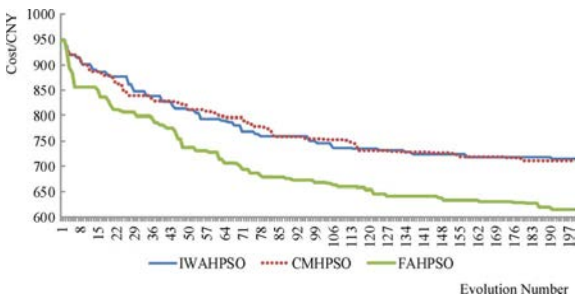

Fig. 11. Iteration curves of three different PSO methods.

TABLE III
EXPERIMENTAL DATA COMPARISON AMONG FOUR AI METHODS

Methods \ Indices	Network Loss(CNY)	Comprehensive Cost(CNY)	Switch Operations	Consumed Time (s)
SA	611	700	178	500
HAS	593	680	174	480
GA	537	618	162	490
FAHPSO	534	614	160	310

TABLE IV
EXPERIMENTAL RESULT COMPARISON BETWEEN FAHPSO AND GA IN OTHER THREE REAL DISTRIBUTION NETWORKS

Methods	Case I		Case II		Case III	
	FAHPSO	GA	FAHPSO	GA	FAHPSO	GA
Network Loss (CNY)	723.5	764.5	961.4	991.6	1187.2	1224.7
Comprehensive Cost (CNY)	832.5	885	1109.9	1150.1	1366.2	1424.2
Switch Operations	218	241	297	317	358	399
Consumed Time (Second)	401	646	458	714	492	751

D. Performance Test of FAHPSO Compared With Other Improved PSO Methods

In order to verify further the performance of FAHPSO algorithm, three different variants of hybrid PSO methods are employed to solve the corresponding MINLP problem of the same distribution network under the same scenario. These three PSO variants are Inertia Weight Approaching (IWA) hybrid PSO [24], Chaos Mutation based hybrid PSO in [28] and the Fuzzy Adaptive inference based hybrid PSO in this paper. In the numerical experiments, the optimization objective is to minimize the comprehensive cost. The corresponding search processes are shown in in Fig. 11.

According to Fig. 11, FAHPSO finds better results than other PSO improved methods. Because of the performance of fuzzy adaptive inference, FAHPSO always escapes local optima and approaches to the optimal solution. It can be seen that 16.3% of the comprehensive cost is saved.

E. Performance Test of FAHPSO Compared With Other Artificial Intelligent Methods

For the further evidence of the performance of FAHPSO, other artificial intelligent (AI) methods, including Simulated Annealing method (SA), Harmony Search Algorithm (HSA), Genetic Algorithm (GA), are used to search the optimal solution of the aforementioned optimization problem together with FAHPSO. In the numerical experiment, the optimization objective is still to minimize comprehensive cost and the number of the total iteration cycles is 200. The corresponding data are shown in Table III.

In Table III, FAHPSO is obviously better than SA and HAS. First, the solution obtained by FAHPSO corresponds to the least comprehensive cost, the least power loss and the least switch operation number. Almost 12.3% and 9.7% of the total comprehensive cost are saved, respectively. Second, the calculation time used by FAHPSO is also the least in the three methods and almost 38% and 35.4% of the consumed time are saved, respectively.

At the same time, FAHPSO and GA perform pretty similarly in terms of power losses, comprehensive costs, and switch operations. However, the consumed time of FAHPSO is much less than the consumed time of GA and almost 38.7% of the consumed time is saved. In order to further compare the performance of FAHPSO and GA, both FAHPSO and GA are applied to other three real distribution systems, which are provided by Chengdu Power Supply Bureau of China, namely, Case I, Case II and Case III. The node numbers of these three real cases are greater than the distribution network shown in Fig. 6, namely, 98 nodes, 127 nodes and 154 nodes. In the numerical experiment, the optimization objective is still to minimize comprehensive cost and the number of the total iteration cycles is also 200. The corresponding experimental data are shown in Table IV.

From Table IV, it can be seen that when the size of distribution network increases, the proposed FAHPSO method begins to perform better than GA in both solution quality and computation speed. Compared with GA, the comprehensive cost is saved by 5.93%, 3.50%, and 4.07%, respectively while the consumed time is reduced by 37.9%, 35.9%, and 34.5%, respectively.

F. Rationality Test of Coupling Reconfiguration of Distribution Network With Reactive Power Control of Distributed Generators

In order to prove the rationality of harmonious use of segmented time network reconfigurations and reactive powers of distributed generators for comprehensive cost minimization, four new cases are employed to test the proposed FAHPSO method. They are called Case A, Case B, Case C and Case D. In Case A, neither segmented-time network reconfigurations nor segmented-time reactive power control of distributed generators are used to minimize the comprehensive cost. Both the network topology and the reactive powers of DGs are fixed.

TABLE V
EXPERIMENTAL RESULT COMPARISON WITH DIFFERENT OPTIMIZATION MEASURES

Indices \ Cases	Case A	Case B	Case C	Case D
Power Loss Cost (CNY)	948	641	756	534
Comprehensive Cost (CNY)	948	702	756	614

TABLE VI
EXPERIMENTAL RESULTS UNDER THE SCENARIOS WITH DIFFERENT RANDOM ERRORS

Indices \ Scenarios	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Power Loss (CNY)	538	541	540	534
Comprehensive Cost (CNY)	618	619	616	614
Consumed Time (s)	334	328	335	310

In Case B, mere segmented-time network reconfigurations are used to optimize the operation of distribution systems. The reactive powers of distributed generators are fixed. In Case C, mere segmented-time reactive powers of distributed generators are used. The network topologies are fixed. In Case D, both segmented-time distribution network reconfigurations and segmented-time reactive powers of distributed generators are used to optimize the operation of distribution systems. The corresponding experimental data are shown in Table V.

According to Table V, it can be seen that the harmonious use of distribution network reconfiguration and reactive powers of distributed generators plays a great role on comprehensive cost reduction. Compared with other three cases, almost 35.2%, 12.5% and 18.8% of the comprehensive cost are saved, respectively.

G. Adaptability Test of the Proposed Method to Forecast Errors

Both the forecast load curves shown in Fig. 10 and the forecast active power curves of distributed generators shown in Fig. 11 include some forecast errors. This paper does not focus on the strategy of dealing with forecast errors, but some numerical experiments are finished to test the reliability of the proposed FAPSO method. Here, a 5% random forecast error is added into forecast load curves and forecast active power curves, respectively. FAHPSO is used to solve the corresponding MINLP problems under four different Scenarios. In Scenario 1, the 5% random error is added only into load curves. In Scenario 2, it is added only into active power curves of distributed generators. In Scenario 3, it is added into both load curves and active power curves. In Scenario 4, it is not added into either load curves or active power curves. The corresponding numerical results are shown in Table VI.

From Table VI, because of the effect of forecast errors, some comprehensive cost differences are produced. They are 0.65%, 0.81%, and 0.32%, respectively. However, the amplitudes of these differences are below 1%. Hence, it may be accepted by most electric power companies.

TABLE VII
EXPERIMENTAL RESULT COMPARISON AMONG THREE LARGE DISTRIBUTION NETWORKS

Indices \ Cases	Network A	Network B	Network C
DG Number	20	38	49
Switch Number	202	497	608
Branch Group Number	48	95	130
Iteration Cycles	200	200	200
Power Loss (CNY)	1607	3735	4537
Comprehensive Cost (CNY)	1847	4289	5219
Consumed Time (s)	535	646	798

H. Adaptability Test of the Proposed Method to Large Distribution Networks

In this part, the proposed FAHPSO are further used to solve the MINLP problems from three large distribution networks called Network A, Network B, and Network C, respectively. These data are provided by Chengdu Power Supply Bureau of China. The target is to test the adaptability of the proposed FAHPSO method to large distribution networks. The relevant important parameters of three distribution networks and some typical indices are shown in Table VII.

According to Table VII, it can be seen that the proposed FAHPSO can be used to solve the MINLP problems of large distribution networks. Although all of the indices become bigger with the increase of the size of distribution networks, the increase trend is not proportional. For example, the size of Network C is almost tripled, compared with Network A, but the consumed time is merely increased by a half. The whole optimization calculation of Network C is finished within 14 min. In most situations of China, it can be accepted. In our experiments, the used computer is a common PC. If the fast industry computer is used or the iteration cycle number is reduced, the consumed time will be further reduced.

V. CONCLUSION

In this paper, the problem of segmented-time distribution network reconfiguration, coupled with optimal reactive power control of distributed generators, is investigated. The main contributions are summarized as follows.

The formulation of segmented-time distribution network reconfiguration coupled with optimal reactive power control of distributed generators is presented. The presented formulation can be applied to large distribution networks.

The strategy of grouping branches is presented to reduce the number of particle property items. By this strategy, a couple of binary property items can be simplified to merely one integer property item. This can accelerate the search process and save the consumed time.

Hybrid PSO method, consisting of two variants of PSO methods, is presented to solve the formulated MINLP problem. The integer PSO is used to deal with the evolution of the sequence number of the OFF branch in the branch groups and the continuous PSO is used to deal with the evolution of reactive powers of distributed generators.

Fuzzy adaptive inference is used to enhance the iteration process by improving the dynamic performance of the inertia weight. As a result, the proposed FAHPSO can escape local optima, effectively.

An improved version of the typical 70-node distribution network and several real distribution networks are used to test the performance of the proposed FAHPSO method. The experimental data show that the proposed FAHPSO can solve effectively the corresponding MINLP problems. At the same time, it also proves that the harmonious use of distribution network reconfiguration and reactive powers of distributed generators is better than any mere use.

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