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Multiobjective Distribution Network Reconfiguration Considering the Charging Load of PHEV

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Abstract—**Energy crisis and environmental pollution make the plug-in hybrid electric vehicle (PHEV) become a hot topic. This paper proposes a multiobjective network reconfiguration methodology based on quantum-inspired binary particle swarm algorithm that aims at alleviating the adverse impact of PHEV on distribution system. The methodology involves two steps: load level division and network reconfiguration for each load level. Two different charging patterns of PHEV are considered in this analysis: uncoordinated charging and coordinated charging. The simulation results show that the proposed methodology is an effective method to make the distribution network more flexible to accommodate PHEV.**

Index Terms—**Distribution network, fuzzy sets, plug-in hybrid electric vehicle**

I. INTRODUCTION

The plug-in hybrid electric vehicle (PHEV) has recently become a popular topic because of the increasing scarcity of energy sources and growing environmental pollution. It is considered to be one of the most feasible technologies to improve energy efficiency and reduce the CO2 emission. However, opportunities and challenges coexist. PHEV brings out many benefits, while the charging demand of PHEV will significantly affect the operation and management of the power grid [1].

Large number of PHEVs will bring great impact on the security and economy of distribution system. It has been shown that PHEV with uncoordinated charging will produce new peak load and increase the supply pressure on distribution system [2]. Some studies also show that massive use of PHEV will increase real power loss and decrease power quality in distribution system [3]. Therefore, some coordinated charging strategies have been proposed for alleviating the adverse impact of PHEV on distribution system [4], [5]. However, there is not a mature market formed for PHEV yet, and the proportion of PHEV users willing to participate the coordinated charging is not clear. All of the PHEVs adopting coordinated charging strategy will be a good thing, but that is unrealistic. Therefore, more methods will be needed to solve the distribution system problems caused by PHEVs' charging. The optimal operation of the system side such as distribution network reconfiguration is an effective means, which can make the grid more flexible to accommodate PHEVs. Electric distribution network is generally designed as a mesh but operated in radial pattern. The utility operator can change the topology of the distribution network for the security of network, minimizing power losses and improving power quality [6]–[9].

In this study, network reconfiguration technique is considered as an approach to alleviate the adverse impact of PHEV on distribution system. This paper considers multiple objectives, which are minimization of energy loss, minimization of voltage drop and load balancing among various feeders. These objectives are transferred into one optimal objective by the fuzzy set theory. Since there are a variety of load levels throughout a day, single implementation scheme of network reconfiguration may not guarantee the system properties of each period to achieve the best. Therefore, it is necessary to plan multiple network reconfigurations for the whole day, especially taking the charging load of PHEV into account. So a process of load level division is performed before finding optimal schedules of network topology.

Quantum-inspired binary particle swarm optimization (QBPSO) algorithm is a novel particle swarm algorithm, inspired by the fundamental theory of particle swarm and features of quantum computing [10]. It preserves the diversity of population, and has faster convergence speed and global optimization ability. QBPSO algorithm is used to get time interval of each load level and find the optimal schedules of distribution network topology.

II. CHARGING LOAD OF PHEV

Since the plug-in concept was put forward, the characteristics of the vehicles' charging load has been extensively studied. First of all, the charging behaviour of PHEV is affected by user's driving habits. To make the simulation more realistic, the travel pattern of PHEV in this

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study is based on the practical data, which is captured by the 2009 National Household Travel Survey (NHTS) of the United States. The database files of this survey can be found online at [11]. In addition, this analysis will focus on the PHEVs which are used mainly for commuting purpose. The basic route of these vehicles is between the work place and home.

Moreover, the charging characteristics of PHEV are also relative with the charging patterns. In this analysis, two different charging patterns are considered: uncoordinated charging and coordinated charging.

Uncoordinated charging: PHEVs may obtain energy from power grid at anytime and anywhere according to the user's willingness. In this charging pattern, an underlying assumption is as follows: as long as PHEVs stop at parking lot or at home, they always plug into grid to charge until the batteries are full or other trips begin.

Coordinated charging: The charging behaviours of PHEVs are controlled by system operator, which aims to alleviate the adverse impact of PHEVs on power system. The system operator collects the information about the start time and distance of next trip from the vehicles stopped at parking lot or home. This information can be estimated by machine based on historical travel pattern or set manually. Then the operator would adjust the PHEVs' charging behaviours to appropriate time when the system has a lower load pressure.

Since the proportion of PHEV users willing to participate the coordinated charging is not clear, it is necessary to simulate the scenarios with various proportions of PHEV adopting the coordinated charging.

III. LOAD LEVEL DIVISION

Distribution network reconfiguration has been extensively studied in the past years. Most of them just consider a specific load level of distribution system. However, load demands of power systems has time-varying characteristic. The optimal operation scheme should change along with the time-varying load demands, correspondingly. Therefore, a process of load level division is firstly performed in this study. All-day load profiles are divided into several intervals according to the "similarity" of hourly load. Thereafter, an optimal operation scheme is determined for each load level. In urban distribution system, the load profiles of different regions have different trends. Fig. 1 shows three typical profiles of residential load, industrial load and commercial load of an urban distribution system. It can be observed that the load demand of various regions have various patterns. The start time and end time of each interval can be determined by optimization process. The objective function is as follows

$$F = \min \sum_{i=1}^{S} \sum_{j=1}^{K_i} [(P_{ij}^R - PA_i^R)^2 + (Q_{ij}^R - QA_i^R)^2 + \\ +(P_{ij}^I - PA_i^I)^2 + (Q_{ij}^I - QA_i^I)^2 + \\ +(P_{ij}^C - PA_i^C)^2 + (Q_{ij}^C - QA_i^C)^2], \quad (1)$$

where P_{ij}^R, P_{ij}^I, P_{ij}^C are active power of the jth load point of the ith load level in residential, industrial and commercial areas; Q_{ij}^R, Q_{ij}^I, Q_{ij}^C are reactive power of the jth load point of the ith load level in residential, industrial and commercial areas; PA_i^R, PA_i^I, PA_i^C are average active power of the ith load level in residential, industrial and commercial areas; QA_i^R, QA_i^I, QA_i^C are average reactive power of the ith load level in residential, industrial and commercial areas; K_i is the number of load points in the ith load level, which subjects to $\sum_{i=1}^{S} K_i = 24$; S is the number of load levels all day, which is determined based on the engineer experience in this study.

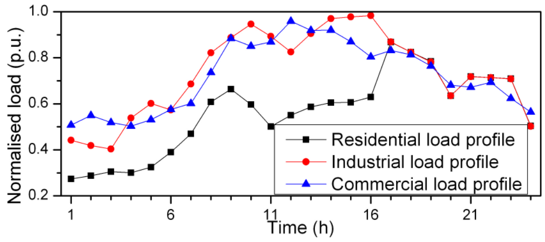

Fig. 1. Normalized load profile of different regions.

IV. FORMULATION OF THE MULTIOBJECTIVE RECONFIGURATION PROBLEM IN FUZZY ENVIRONMENT

The fuzzy set theory is used to achieve multi goals of distribution network reconfiguration simultaneously. The membership function is used as a measure of each objective, whose degree is limited in the interval [0, 1]. The higher degree of membership indicates higher satisfaction of the solution. The trapezoidal function is chosen to describe the value of each objective mentioned in the paper, which can be defined as

$$\mu(f_i) = \begin{cases} 1, & f_i < f_i^{\min}, \\ \dfrac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} < f_i < f_i^{\max}, \\ 0, & f_i > f_i^{\max}, \end{cases} \quad (2)$$

where $\mu(f_i)$ is the function for each objective f_i. $f_i^{\min}$ and $f_i^{\max}$ are the lower and upper bounds of the objective function. A plot of the membership function is shown as Fig. 2.

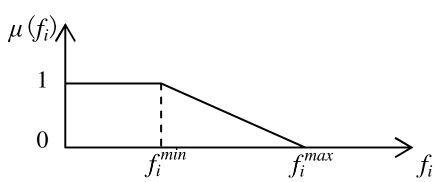

Fig. 2. An example of membership function.

The objectives and constrains can be expressed as follow:

1) Energy loss reduction.

The first objective is minimizing the energy loss

$$f_1 = \sum_{t=1}^{24} Ploss^t \cdot \Delta t / \sum_{t=1}^{24} Ploss_0^t \cdot \Delta t, \quad (3)$$

where $Ploss^t$ denotes the power loss after network reconfiguration at time t, and $Ploss_0^t$ denotes the power loss before network reconfiguration at time t. Δt denotes the period between two time points and is set to be 1h in the paper.

2) Bus voltage quality.

Bus voltage is one of the most significant indicators of the service quality, and the second objective is maximizing the bus voltage quality

$$f_2 = \max\{V_i^t - Vs\}, (t = 1,2,\cdots,24; i = 1,2,\cdots,N), \quad (4)$$

where V_i^t is the p.u. voltage on ith bus at time t, and Vs is the rated voltage, N is the number of system nodes. f_2 is the maximum value of voltage deviation of all nodes. Lower f_2 indicates higher quality of bus voltage.

3) Load balance of transformers.

The index of the load balance between the transformers is calculated:

$$f_3 = \max\{S_i^{load,t} / S_i^{rate}\}, (t = 1,2,\cdots,24; i = 1,2,\cdots,M), \quad (5)$$

where $S_i^{load,t}$ is the actual loading of the ith transformer at time t, S_i^{rate} is the rated loading of the ith transformer, M is number of transformers . f_3 is the maximum value of load ratio of all transformers. Lower f_3 indicates higher security.

4) Constrains.

The radial structure of the network must be maintained during the reconfiguration. All loads must be served, regardless of the action of switches.

The multi-objective problem often consists of several conflicting goals that cannot be achieved simultaneously. Finding a compromise solution is much more realistic than searching for a solution such that every objective is optimal. In fuzzy domain, the aggregation operators are usually used to gather each objective's value into the global evaluation of the membership degree for whole objectives [12]. The geometric mean operator is used in this study

$$\mu(f_1,\cdots,f_n) = (\prod_{i=1}^{n} \mu(f_i))^{1/n} \quad (6)$$

where $\mu(f_i,\ldots,f_n)$ is the degree of synthetic membership and n is the total number of the objectives.

V. Illustration of Quantum-Inspired Binary Particle Swarm Optimization Algorithm

QBPSO is a novel particle swarm algorithm, inspired by the fundamental theory of particle swarm and features of quantum computing [10]. It preserves the diversity of population, and has faster convergence speed and global optimization ability.

In QBPSO, quantum bit (Q-bit) is defined as the smallest unit, which may be in the "1" state or "0" state. A Q-bit is described by a pair of numbers (α , β), which satisfy the constraint $\alpha^2 + \beta^2 = 1$. A Q-bit particle as a string of n Q-bits can be defined as follow

$$p_i = \left[\begin{array}{c|c|c|c} \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{in} \\ \beta_{i1} & \beta_{i2} & \cdots & \beta_{in} \end{array}\right], \quad (7)$$

where $\alpha_{ij}^2 + \beta_{ij}^2 = 1$, $j = 1,2,\cdots,n$. The state of the jth element in particle p_i takes a value of 0 or 1 by the probability of α_{ij}^2 or β_{ij}^2 . In the initialization step, both α and β of each particle equal to $1/\sqrt{2}$ in order to make "0" state and "1" state occur with equal probability.

The position vector of ith particle $X_i=\{x_{i1},\ldots, x_{im}\}$ is determined by the value of β_{ij}^2 stored in the ith Q-bit string

$$x_{ij} = \begin{cases} 1, & rand_j < \beta_{ij}^2, \\ 0, & otherwise, \end{cases} (j = 1,2,\cdots m,) \quad (8)$$

where $rand_j$ is random number uniformly distributed between 0 and 1. m is the length of the Q-bit string.

Instead of velocity updating in traditional particle swarm optimization, rotation angle updating is used in QBPSO. Determining the rotation angle requires information including the current position, the best position of the ith particle and the group's best position so far

$$\Delta\theta_{ij}^{k+1} = \theta \times \{\gamma_{1i}^k \times (x_{ij}^{P,k} - x_{ij}^k) + \gamma_{2i}^k \times (x_j^{G,k} - x_{ij}^k)\}, \quad (9)$$

where θ is the magnitude of rotation angle, γ_{1i}^k and γ_{2i}^k are two factors determining direction of evolution towards individual best and group best, $x_{ij}^{P,k}$ is the personal best of the jth element in the ith particle, $x_j^{G,k}$ is the group best of the jth element, x_{ij}^k is the current position, k is the current iteration number.

The magnitude of rotation angle θ affects the performance of the algorithm. The values from 0.001π to 0.05π are recommended for θ, and a dynamic rotation angle approach is adopted for enhancing the convergence characteristics

$$\theta = \theta_{\max} - (\theta_{\max} - \theta_{\min}) \times \frac{k}{K_{\max}}, \quad (10)$$

where k is the current iteration number, $K_{\max}$ is the maximum iteration number, $\theta_{\min} = 0.001\pi$ and $\theta_{\max} = 0.05\pi$.

The factors γ_{1i}^k and γ_{2i}^k can be obtained in the following way:

$$\gamma_{1i}^k = \begin{cases} 0, Fit(X_i) \geq Fit(Pb_i^k), \\ 1, \quad otherwise, \end{cases} \quad (11)$$

$$\gamma_{2i}^k = \begin{cases} 0, Fit(X_i) \geq Fit(Gb^k), \\ 1, \quad otherwise, \end{cases} \quad (12)$$

where $Fit(*)$ is the fitness of the particle, Pb_i^k is the personal best of ith particle, Gb^k is the group best.

The Q-bit is updated by rotation gate as following:

$$\begin{bmatrix} \alpha_{ij}^{k+1} \\ \beta_{ij}^{k+1} \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_{ij}^{k+1}) & -\sin(\Delta\theta_{ij}^{k+1}) \\ \sin(\Delta\theta_{ij}^{k+1}) & \cos(\Delta\theta_{ij}^{k+1}) \end{bmatrix} \begin{bmatrix} \alpha_{ij}^{k} \\ \beta_{ij}^{k} \end{bmatrix}, \qquad (13)$$

In this work, QBPSO is used for two optimal processes of load level division and network reconfiguration. It is necessary to illustrate how QBPSO works. One of the most important things is the coding strategy for these two optimizations, which should be well considered.

1) Coding scheme for load level division.

It is not difficult to obtain 24 forecasted load points of the next day using existing load forecast technique. If the number of load levels is set to *S*, the mission of the optimization algorithm is finding *S*-1 time points to divide the whole load curve. Since a string of Q-bit must be binary, the coding process for load level division is shown as follow:

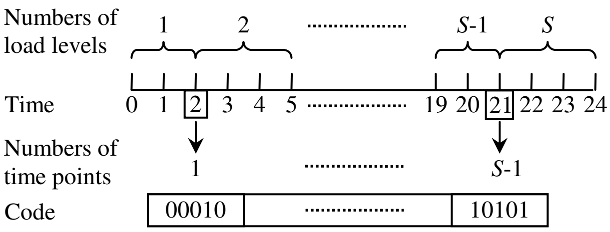

Fig. 3. Coding scheme for load level division.

2) Coding scheme for network reconfiguration.

It is very important to choose an adaptive coding method when applying modern heuristic algorithm in the distribution reconfiguration problem. In this work, an efficient variable expression is used. First of all, all the sectionalizing switches and tie switches are closed. Then the fundamental loops of the meshed network are identified. According to engineering experience and graph theory, the network will maintain radial with one switch open in each loop. Therefore, the coding scheme is to make a string of variables representing the open switches in each fundamental network loop.

Let us consider a 9-bus system shown in Fig. 4. There are 3 fundamental loops in this network, and the switch sets for each loop are shown in Table I. Three switches from each set have to be opened to form a radial network. For example, a group of open switches {2, 8, 4} is a feasible solution. But the real code {2, 8, 4} is not suitable for QBPSO, which has to be converted into binary. The conversion process is as follows:

1) Sort the switches' numbers from small to large in each switch set.
2) Identify the sort position of the open switch in each set.
3) Convert the number of the sort position to binary code.

However, this encoding strategy may still generate unfeasible solutions. Therefore, some heuristic strategies are used to repair the infeasible solutions:

1) Two adjacent loops have some common switches. If a common switch is selected in two loops at the same time, it should be replaced by a new switch from one of these adjacent loops.
2) The implementation of network reconfiguration also requires all loads be served. So the solution will be re-generated, once isolated nodes are found.

The schematic flowchart of the QBPSO and the main procedure are shown in Fig. 5 and Fig. 6.

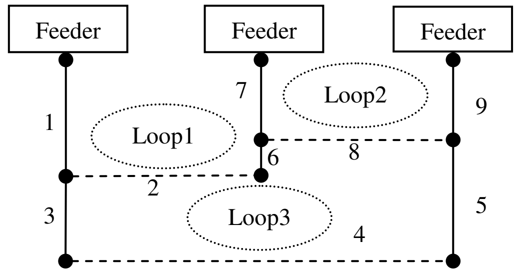

Fig. 4. 9-bus system.

TABLE I. CODING SCHEME FOR NETWORK RECONFIGURATION.

Loop	1	2	3
Switch set	1,2,6,7	7,8,9	2,3,4,5,6,8
Open switch	2	8	4
Order in the set	2	2	3
Coding scheme	010	10	011

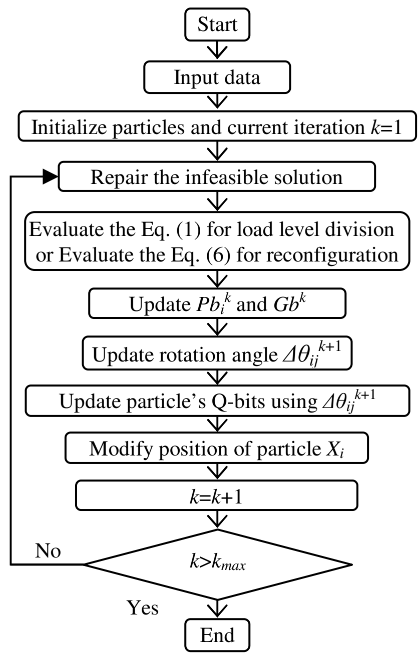

Fig. 5. Flowchart of the QBPSO.

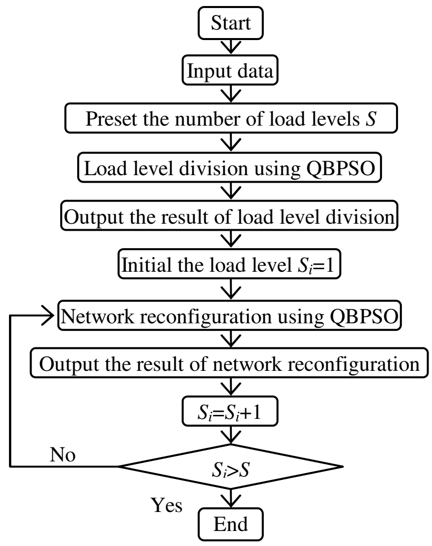

Fig. 6. Flowchart of the main program.

VI. CASE STUDY

The test system is a 11-kV 33-node system, and its data is given in [13]. The simulation is carried out using Matlab environment and MATPOWER software package.

To check the performance of QBPSO, a test of network reconfiguration without considering the charging load of PHEV is carried out. Only one objective of energy loss reduction is considered in this case, and the lower and upper bounds of the membership function $f_i^{\min}$ and $f_i^{\max}$ are 0.5 and 1.0, respectively. The time interval is assumed to be 1h. Before network reconfiguration, the total energy loss of this system is 203 kWh. Table II summarizes the results obtained by QBPSO and other methods including GA and PSO. For each algorithm, 100 independent trials are performed to compare the solution quality and convergence characteristics. The population sizes of these algorithms are 30, and the maximum number of generation is 100. The crossover rate of GA is 0.8. The mutation rate is initialized to 0.25 and decreased in the steps of 0.01, till the final rate of 0.05 is achieved. The acceleration coefficients of PSO are set to 2.0. Average energy loss convergence curves of the algorithms are shown in Fig. 7.

It is observed that the performance of QBPSO is much better than the other methods. However, the time consumed by QBPSO is slightly more than other algorithms. That is because the conversion between real code and binary code for QBPSO requires a little time.

TABLE II. COMPARISON OF THE ALGORITHMS' PERFORMANCE.

Method	Energy loss (kWh)			Best result out of 100 runs	Mean Time (s)
	Best	Worst	Mean		
GA	139.7	145.2	141.0	60%	30.0
PSO	139.7	145.7	141.3	55%	28.5
QBPSO	139.7	141.3	139.8	95%	31.7

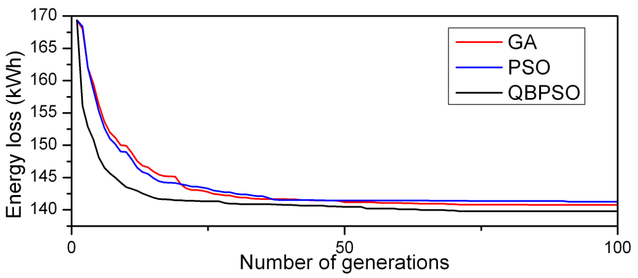

Fig. 7. Convergence situation of different algorithms.

Then, multiobjective optimal network reconfiguration considering the charging load of PHEV is performed. It is assumed that the peak load of the test system is proportional to that of the U.S. in winter and the ratio is approximately 0.0056‰ [14]. The vehicle number of the test system is assumed to be proportional to the number of registered cars in the U.S. and the ratio is also 0.0056‰ [15]. Therefore, it is assumed that there are 1380 registered cars in the test system. The market penetration of PHEV is assumed to be 20%. The travel data of the PHEV is a random sample of the data in NHTS. "PHEV-x" is used to distinguish the types of PHEV, which represents a PHEV that, starting with a fully charged battery, can travel x miles in electric driven mode without consuming any fuel in the tank. The type of PHEV is determined by average miles of the PHEV per day, and the percentage of PHEV with different battery capacity is shown in Table III. It is assumed that all of charging infrastructures installed in every node are 2kW charger, because the test system is a small-scale distribution system. The original load data is used as reference value of each load point, and the normalized load profile of the three load areas in the test system has shown in Fig. 1.

The objective of load balance of the transformer is not considered, because the test system has only one transformer. The values selected for lower and upper bounds of the membership function of objectives involved are given in Table IV.

TABLE III. THE PERCENTAGE OF PHEV WITH DIFFERENT BATTERY CAPACITY.

Vehicle Type	PHEV20	PHEV40	PHEV60
Percentage	46%	28%	26%
Battery capacity /kWh	6	12	18

TABLE IV. LOWER AND UPPER BOUNDS OF THE MEMBERSHIP FUNCTIONS.

Objectives	f_i^{min}	f_i^{max}
Power Loss Reduction	0.5	1.0
Bus Voltage Quality	0.05	0.1

Fig. 8 shows the energy loss before and after network reconfiguration. "S=1" represents that the load division process is not performed and just one topology scheme is used for distribution network throughout the whole day. "S=4" represents that the load curve is divided into 4 segments. It is observed that, without network reconfiguration, coordinated charging strategy contributes to the reduction of energy loss. With the increasing proportion of the PHEV willing to adopt coordinated charging, the energy loss is gradually reduced. By using network reconfiguration technique, the energy loss of the system can be further reduced. According to the enlargement of the graph, it can also be seen that multiple implementation of network reconfiguration can save more energy loss than single implementation can.

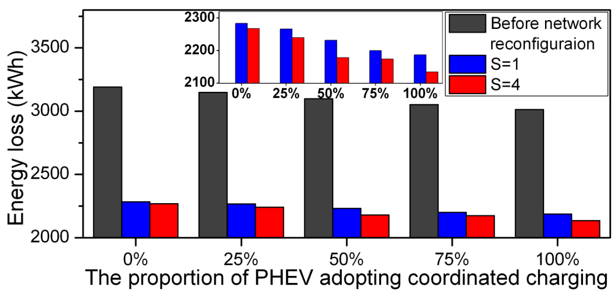

Fig. 8. Energy loss of distribution system.

Fig. 9 shows the minimum voltage appearing during the whole day with distribution network reconfiguration.

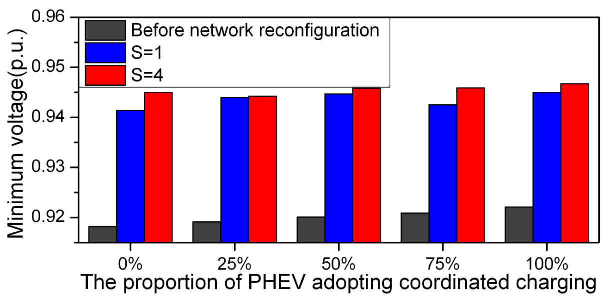

Fig. 9. Minimum voltage appearing during the whole day.

The result shows that the implementation of network reconfiguration can significantly improve the voltage quality of distribution system. Also, multiple implementation of network reconfiguration can achieve a better result than single implementation can.

VII. CONCLUSIONS

In this study, network reconfiguration technique is considered as an approach to alleviate the adverse impact of PHEV on distribution system. The scenarios with various proportions of PHEV adopting the coordinated charging are simulated. A formulation to reduce energy loss, improve power quality and balance the load of transformers is presented in fuzzy sets, and QBPSO algorithm was implemented to obtain the optimal solution.

The simulation results show the good performance of QBPSO in the network reconfiguration problem. It is also shown that network reconfiguration technique is an effective method to make the distribution network more flexible to accommodate PHEVs.

Load level division technique is used in this study, and multiple operation schemes are needed due to the time-varying load demands. The simulation results show the multiple implementations of network reconfiguration have better results than the single implementation does. In this study, the number of load level is obtained just based on experience. The future work should find a way to determine the optimum number of load levels.

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