Optimal Switch Placement in Distribution Systems Using Trinary Particle Swarm Optimization Algorithm

Adel Moradi and M. Fotuhi-Firuzabad, *Senior Member, IEEE*

***Abstract*—Achieving high-distribution reliability levels and concurrently minimizing capital costs can be considered as the main issues in distribution system optimization. Determination of the optimum number and location of switches in distribution system automation is an important issue from the reliability and economical points of view. In this paper, a novel three-state approach inspired from the discrete version of a powerful heuristic algorithm, particle swarm optimization, is developed and presented to determine the optimum number and locations of two types of switches (sectionalizers and breakers) in radial distribution systems. The novelty of the proposed algorithm is to simultaneously consider both sectionalizer and breaker switches. The feasibility of the proposed algorithm is examined by application to two distribution systems. The proposed solution approach provides a global optimal solution for the switch placement problem.**

***Index Terms*—Distribution system, particle swarm optimization (PSO), reliability cost/worth index, switch placement.**

I. Introduction

The percentage of system faults in a distribution network is more compared than that in other parts of a power grid system [1]. The reduction of momentary and sustained outages reacting more quickly to system disturbances can be achieved by protection schemes and leading-edge equipment, such as modern remote-controlled switches, breakers, reclosers, and fault indicators. In order to achieve a high level of reliability, more investment should be accomplished by the utilities and the best locations for installing these switches should be found so that the most possible benefit is gained.

Automatic and remote-controlled switches play prominent rules in automated distribution systems. Switching devices are located in primary distribution systems for various purposes (e.g., to isolate failed components and faults in emergency states, to minimize interruption time and costs, to minimize system losses by network topology reconfiguration in the normal states, and in summary to improve overall system reliability).

Determination of the best switch locations in a distribution system is an optimization problem. In this and other engineering problems, two major obstacles limiting the solution efficiency are frequently encountered. First, these kinds of problems can be computationally time consuming. Second, engineering optimization problems are often plagued by multiple local optima, requiring the use of global search methods, such as population-based algorithms, to deliver reliable results [2].

Heuristic evaluation techniques, such as the genetic algorithm (GA), ant colony algorithm, and tabu search [5]–[7] have been widely used in engineering disciplines to solve a wide range of combinatorial problems, such as control system designing, neural-network training, power system analysis, etc.

An optimum switch rearrangement problem is solved in [6] using a cooperative agent algorithm, the ant colony system (ACS), and the results are compared with a GA-based method. In [5], an optimum number of switches in a distribution system is obtained by cost/worth analysis on the system, and optimum locations of switches are found by the simulated annealing algorithm. In [7], a numerical two-stage decomposition approach is developed to divide the solution space into independent subspaces. The optimization problem of finding optimum locations for switches is then solved in each subspace.

Particle swarm optimization (PSO) is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling [3]. The PSO technique is considered to have fewer parameters than a standard GA and is highly resistive to stop at local optimization points in favor of global ones [4]. This technique has been used as an optimization algorithm in a number of engineering problems [8]–[10].

The application of the PSO algorithm for reactive power and voltage control considering voltage security assessment is illustrated in [9], where the feasibility of the proposed method is demonstrated and compared with a reactive tabu search and the enumeration method by applying it to practical power system models. In [10], the PSO technique is used as a tool for loss reduction calculation and determines the required amount of shunt reactive power compensation that takes place in each bus.

In the studies presented in different literature, the determination of the number and location of only one type of switch, mainly sectionalizers, is taken into account. Concurrently, employing other types of switches, such as circuit breakers (CBs), could have a positive impact on system reliability. In the previously mentioned studies, CBs are normally located in the predetermined positions in the feeders by default. In this paper, the determination of the optimum number and location of two types of switches (i.e., CB and sectionalizer) is formulated as

Manuscript received March 17, 2006; revised November 16, 2006. Paper no. TPWRD-00150-2006.

A. Moradi is with the Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran.

M. Fotuhi-Firuzabad is with the Center of Excellence in Power System Control and Management in the Electrical Engineering Department, Sharif University of Technology, Tehran, Iran (e-mail: fotuhi@sharif.edu).

Digital Object Identifier 10.1109/TPWRD.2007.905428

an optimization problem. A novel multistate version of a discrete PSO algorithm is presented in this paper to determine the optimum number and locations of CBs and sectionalizers in a distribution system.

The convergence rate and the ability of the proposed algorithm for finding near global minimum are tested on the RBTS BUS 4 and the IEEE 123-node feeder standard test system.

II. PSO Algorithm

A. Continuous Version of PSO

Particle swarm is an algorithm for finding optimal regions of complex search spaces through the interaction of individuals in a population of particles. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of individual vectors, designated as “particles.” The individual particles are conceptualized as moving points in a multidimensional space. They are drawn stochastically toward the positions of their own last best performance and the best last performance of their neighbors. The algorithm was originally developed for nonlinear optimization problems with continuous variables. However, it can be easily expanded to treat problems with discrete variables [9].

Some of the principles and advantages of PSO algorithm are as follows.

1) PSO is based on the principle that the probability of finding a better minimum near the so far found minimum is more than the other places. The particles (solutions) are therefore diverted toward searching around the found minimum.

2) PSO is a history-based algorithm such that in each step, particles use their own behavior associated with the previous iterations.

3) Compared to the other evolutionary optimization algorithms, such as GA, PSO is easy to implement and there are few parameters to be adjusted.

Fig. 1 shows the structure of a swarm population in which each swarm is considered an $M \times N$ matrix. In this matrix, M and N are, respectively, the number of agents (swarm size) and number of particles in each agent (swarm dimension).

It is clear that the greater number of agents (M) there are, the more search there is over the solution space. There is, however, a tradeoff between the convergence rate and the computation time required for each iteration calculation. Therefore, the swarm sizes more than a specific number does not have special effect on the algorithm performance. N is determined based on the number of variables of the problem that should be optimized in the algorithm. In the particular problem presented in this paper, N is equal to the number of candidate positions for installing switches.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In each generation, each particle is updated by the following two “best” values. The first one is the best solution obtained by each agent itself in all of the previous generations and is designated as the particle best solution pbest.

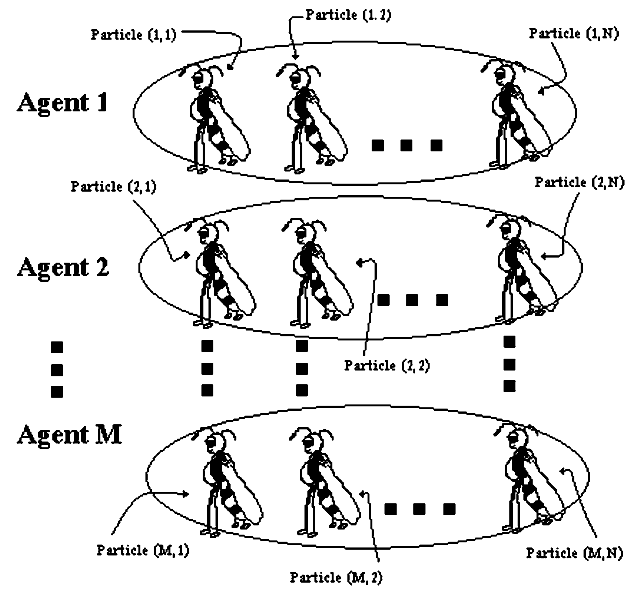

Fig. 1. Structure of a swarm population.

Another “best” value that is tracked by the PSO is the best value obtained by any agent in all previous iterations. This best value is a global best solution and called gbest. Once these two best values are found, the swarm updates its velocity and position using (1) and (2)

$$\begin{aligned} V(t+1) = & V(t) + c_1 \times \mathrm{rand}_{1,t} \\ & \times (\mathrm{pbest}(t) - X(t)) + c_2 \\ & \times \mathrm{rand}_{2,t} \times (\mathrm{gbest}(t) - X(t)) \qquad (1) \\ X(t+1) = & X(t) + V(t+1). \qquad (2) \end{aligned}$$

where

t	iteration number;
$V(t)$	particle velocity at iteration number t;
$X(t)$	particle position at iteration number t;
$\mathrm{pbest}(t)$	particle best solution at iteration number t;
$\mathrm{gbest}(t)$	global best solution at iteration number t;
$\mathrm{rand}_{1,t}$	random number one, between (0, 1) at iteration number t;
$\mathrm{rand}_{2,t}$	random number two, between (0, 1) at iteration number t;
c_1, c_2	learning factors.

The learning factors c_1, c_2 have considerable impacts on the algorithm convergence rate and must be tuned up experimentally. Usually $c_1 = c_2 = 2$. Further information for the continuous version of PSO can be found in [9].

B. Discrete Binary Version of PSO

The main concept of the discrete binary version of PSO is the same as continuous one. In the binary version [11], PSO is modified as

$$V_{i+1} = V_i + c_1 \times \mathrm{rand}_{1,i} \times \Delta V_{i,1} + c_2 \times \mathrm{rand}_{2,i} \times \Delta V_{i,2} \quad (3)$$

where

$$\Delta V_{i1} = \mathrm{pbest}_i - X_i \quad (4)$$
$$\Delta V_{i2} = \mathrm{gbest}_i - X_i. \quad (5)$$

While parameters pbest_i and gbest_i and X_i can take any real value in (1), these parameters are integers in $\{0, 1\}$ in (3). V_i is limited to the interval $[0.0, 1.0]$ as it is a probability not velocity. A logical transformation $S(V_i)$ can be used to accomplish this last modification. The resulting change in the position is then defined by the following rule:

$$X_i = \begin{cases} 1, & \mathrm{rand}(0,1) < S(V_i) \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

$$S(V_i) = \frac{1}{1 + \exp(-V_i)} \quad (7)$$

where

- $S(V_i)$ sigmoid limiting transformation;
- $\mathrm{rand}_{(0,1)}$ random number uniformly distributed in the interval $[0, 1]$;
- V_i probability of X_i being 1 or 0.

First, each particle of a swarm is randomly initiated in state 0 or 1 and the objective function value is calculated for this state arrangement. For each iteration, pbest is found based on the results calculated for each agent of particles, and gbest is calculated based on all previous iterations. Then, in the next iteration, two partial probability values (ΔV_i) are added on or subtracted from the previous probability of each particle. Therefore, the values of $\Delta V_{i1} = \mathrm{pbest}_i - X_i$ and $\Delta V_{i2} = \mathrm{gbest}_i - X_i$ in (3) are small changes of probability in each iteration that can be -1, 0, or 1.

So sigmoid transformation only transforms V_i from the interval $[-\infty, +\infty]$ to $[0, 1]$. It is clear that by adding or subtracting the previous experiences to V_i, the previous experiences and histories are tracked and finally based on the V_i index, where X_i becomes 0 or 1.

This algorithm is suitable for variables that can take only two states 0 or 1; it is therefore applicable when only one type of switch is placed in the network. In this case, for each location, there are two states.

1) state 1: there is a switch in the location.
2) state 0: there is not a switch in the location.

In order to include two types of switches—sectionalizer and breaker—in the optimization process, a novel Trinary version of discrete PSO (TPSO) is developed in the next section, in which each particle and solution space can take three states.

III. Proposed Discrete Multistate Version of PSO

As discussed earlier, particles in PSO are diverted toward the global best minimum based on the experiences of the previous iterations. The algorithm should have a mechanism to memorize experiences and previous histories of particles and use this memory in the decision-making procedure.

The algorithm mentioned before and given in [11] is a binary version of the discrete PSO in which only two states $\{0, 1\}$ can be considered for a candidate position for each switch installation point (i.e., there is a switch in the position or there is not).

Consider that the discrete version of the particle swarm algorithm has to be adopted to determine optimum switch locations when two types of switches—breaker and sectionalizer—exist. In this case, for each location, there are three possible states:

1) installing a breaker;
2) installing a sectionalizer;
3) none of them (installing nothing in that position).

The optimization process should therefore be modified so that it can handle this problem and make a decision on the three possible states.

It should be noted that the operation and protection procedure of these two types of switches are completely different. Relative locations of these switches in the network have considerable impacts on interruption cost index and performance of distribution system in delivering power to customers. Optimum placement of these different kinds of switches in the network must be accomplished simultaneously and the reliability cost/worth function should be minimized considering them concurrently.

A concept of phasor is used in the proposed algorithm, in which the three states are represented by three unity vectors of $1\angle -120^\circ$, $1\angle 0^\circ$, and $1\angle 120^\circ$.

In the first step, each candidate switch location is randomly initiated in one of three possible states. Equation (3) in the binary discrete algorithm is modified as expressed in (8)

$$V_{i+1} = V_i + c_1 \times \mathrm{rand}_{1,i} \times \mathrm{pbest}_i + c_2 \times \mathrm{rand}_{2,i} \times \mathrm{gbest}_i \quad (8)$$

where c_1 and c_2 are constant coefficients. They are chosen based on how much a swarm trusts on itself experiences (c_1) or neighbor's best (c_2).

In (8), the phase of V_i memorizes experiences and solutions from the previous iterations, while in the binary version, the magnitude of V_i contains this information.

The vectors begin with zero coordinates. If the number of repetitions of one state increases, the resulting vector converges to that state. In this case, the rate of converging to the final steady state should only be modified by an appropriate transformation to the stop algorithm from trapping in local minimums.

The phase of V_i is calculated and transformed to interval $[0, 1]$ as the probability of states. So the angles of states $1\angle -120^\circ$, $1\angle 0^\circ$, and $1\angle 120^\circ$ are mapped to 1/6,1/2,5/6, respectively, as shown in Fig. 2. These numbers (1/6, 3/6, 5/6) are indices that angles of vectors converge toward one of them and the final state of each candidate position is determined. In the next step, the difference between the phase of V_i and the three numbers (1/6, 3/6, 5/6) is calculated in each iteration.

The resulting numbers $(d1, d2, d3)$ are transformed using

$$T_1(d_k) = \frac{a.\exp(\tan(\pi(0.5 - d_k)))}{1 + a.\exp(\tan(\pi(0.5 - d_k)))} \quad (9)$$

where d_k is one of the distances $d1$, $d2$, $d3$, and a is a constant number for tuning up the convergence rate of the problem.

This equation is actually sigmoid transformation in the binary PSO that has been modified and adopted for the range of distances in $[0, 1]$. As shown in Fig. 3, constant a is chosen so

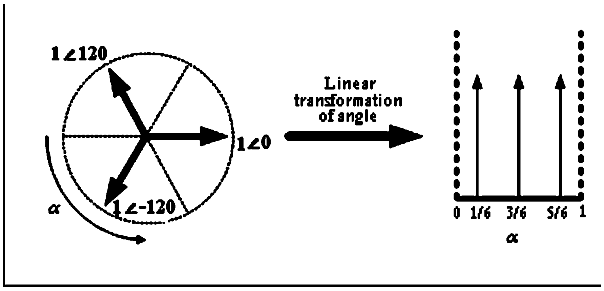

Fig. 2. Vector concept of the proposed algorithm.

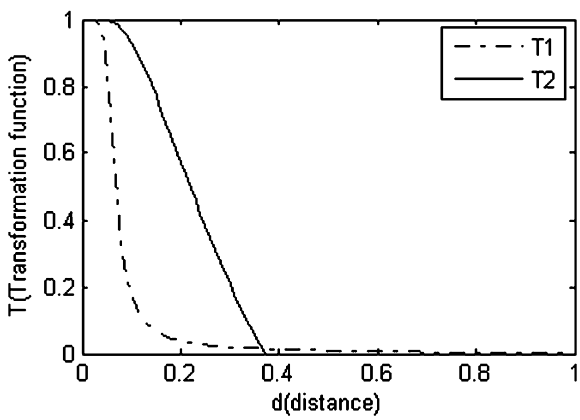

Fig. 3. Transformations used in the proposed algorithm.

that for $d_k > 0.34$, $T_1(d_k) \approx 0$. The reason for this is that the distance from one state index to the next close state index is 1/3.

Another experimental function that has been used in this study is given by (10)

$$T_2(d_k) = \left(1 - \exp\left(1 - \frac{1}{c \times d_k}\right)\right) \tag{10}$$

where $\boldsymbol{c}$ is a constant number for tuning the function. The preference of this transformation over (9) is that it is more symmetrical around 1/6 and $T_2(1/6) \approx 0.5$. Constant c is chosen in such a way that function T2 approaches 0 for $d_k \approx 0.34$.

As noted earlier, the main reason for using these transformations is to control and regulate the convergence rate of the problem and to map the V_i range in the interval $[0, 1]$. As shown in Fig. 3, when a distance approaches zero, the transformed number is limited toward 1. This means that the probability that this state to be selected for the next iteration is about 1, and when distance is about 0.34, then with $a \approx 0.01$ or $C \approx 3$, $T_{1,2}(0.34) \approx 0$. In other words, when the distance from a state index is approximately 0.34, the probability is that this state to be selected is close to zero.

A chance for the global optimizer should always be considered in the algorithm to prevent the algorithm from trapping in a local minimum.

The algorithm is therefore continued as below.

Generate a random number r in the interval $[0, 1]$.

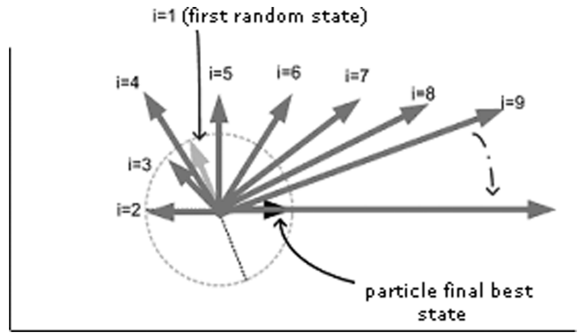

Fig. 4. Convergence process of one particle to its final state.

If ($r > T(d_1)$ and $r > T(d_2)$ and $r > T(d_3)$) or ($r < T(d_1)$ and $r < T(d_2)$ and $r < T(d_3)$), then randomly choose one state for the next iteration.

If ($r > T(d_1)$ and $r > T(d_2)$ and $r > T(d_3)$), then choose the state associated with $d1$ $(1\angle -120^\circ)$ as the state of the next iteration (the same decision for the similar states)

If ($r < T(d_1)$ and $r < T(d_2)$ and $r < T(d_3)$), then randomly choose one of the two states associated with $d1$ and $d2$ as the state of the next iteration.

Then, by evaluating the objective function for each agent set, pbest_i and gbest_i for that iteration are chosen. Fig. 4 shows a typical process of magnitude and phase variation of each particle's probability from the first random state to its final state.

The flowchart of the algorithm is shown in Fig. 5 in which NItr, i, and j are, respectively, the number of the algorithm iterations, iteration number, and agent number.

IV. Distribution Problem Formulation

The objective function of the optimum switch number and placement problem is to minimize the sum of interruption and investment costs for distribution feeders. A number of reliability indices, such as system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), expected unsupplied energy due to power outages (EENS), and system expected outage cost (ECOST) can be calculated for a distribution system.

According to the type and configuration of the distribution system, customer classes, number of customers, customer damage function (CDF), and load diversity of customers, appropriate reliability indices should be chosen as an objective function.

In this paper, the customers' expected outage cost (ECOST) is used as an interruption cost reliability index that should be minimized using a modified version of a discrete PSO algorithm. ECOST is used as the objective function as it responds to the effects of system topology, interruption duration, load variations, and component random failures. It also recognizes various customer types and their nonlinear customer damage functions [5].

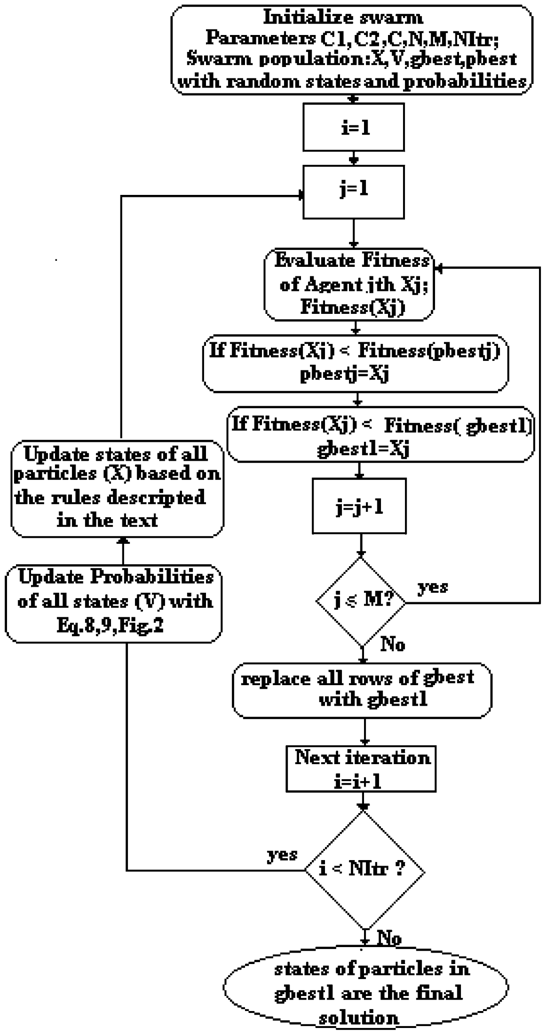

Fig. 5. Flowchart of the algorithm.

The system ECOST can be expressed as follows:

$$\mathrm{ECOST} = \sum_{j=1}^{NC}\sum_{k=1}^{NIL} L_{kj} \cdot C_{jk}(r_j) \cdot \lambda_j \left(\frac{\$}{yr}\right) \tag{11}$$

where

NIL	number of isolated load points due to contingency j;
NC	number of contingencies;
L_{kj}	curtailed load at load point k due to contingency j;
r_j	average outage time due to contingency j;
λ_j	average failure rate of contingency j;
$C_{jk}(r_j)$	outage cost in $(\$/KW)$ of load point k due to outage j with outage duration of r_j.

The cost $C_{jk}(r_j)$ can be obtained from the CDF. System reliability increases as the number of switches is increased. However, factors, such as capital investment cost, installation, and maintenance costs of switches must be considered in conjunction with the benefit derived by implementing additional switches.

The problem of optimization can be described as

$$\begin{aligned}\text{Minimize}[\text{Total.Cost} = \mathrm{ECOST}(&x_1, x_2, x_3, \ldots, x_n,\\ &y_1, y_2, y_3, \ldots, y_m) + n \times \mathrm{SEC} + m \times \mathrm{BRC}]\end{aligned} \tag{12}$$

where

ECOST	expected interruption cost;
x_i	ith location where a sectionalizer is installed;
y_i	ith location where a breaker is installed;
n	number of sectionalizers;
m	number of breakers;
SEC	cost associated with a sectionalizer;
BRC	cost associated with a breaker.

It has to be noted that the cost associated with sectionalizers and breakers includes capital cost, installation cost, and maintenance cost. It is assumed that there are wholly N possible locations for installing switches in the network. The cost function is therefore minimized for the optimum number and locations of switches given that $m + n \geq N$.

For adopting this optimization problem with the TPSO algorithm, N suitable locations for installing switches in the network are considered as the swarm dimension. Each agent of the swarm consists of N particles such that after final optimization, each particle state converges to one final state indicating that a breaker, a sectionalizer, or none of them should be installed in that position.

V. Solution Algorithm

For a given contingency j, the following procedure is used to calculate system ECOST assuming that alternative paths are provided using normally open switches:

Step 1) consider a contingency j;

Step 2) find the first CB in the path toward the feeder;

Step 3) disconnect the faulty zone by this CB. A faulty zone is a zone associated with the primary protection zone of a failed component—transformer or transmission line.

Step 4) find the first sectionalizing switch in the path toward the feeder If there is not any sectionalizing switch in the path before the breaker, go to the next step; otherwise, go to Step 6).

Step 5) find all load points which are de-energized by the CB trip and calculate ECOST using (11) for the repair time required to restore energy (t_{rep}), then go to Step 1);

Step 6) find all load points which are de-energized by the CB trip and calculate ECOST using (11) for the switching time of remote-controlled (RC) sectionalizers; (t_{sec})

Step 7) disconnect the RC sectionalizing switch and connect the CB and find new load points which are de-energized and calculate ECOST for the switching time of loop switch (t_{tie}) to restore energy from alternative paths;

Step 8) connect the loop switch and determine the ECOST for the repair time required for the remaining faulty zone;

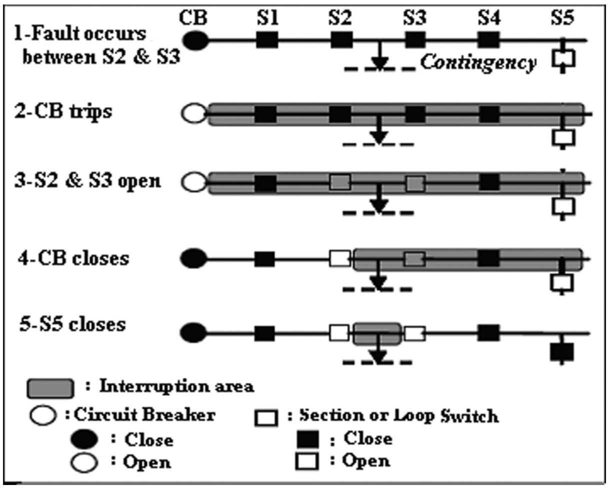

Fig. 6. Process of switching intervals to isolate a fault between $S2$ and $S3$.

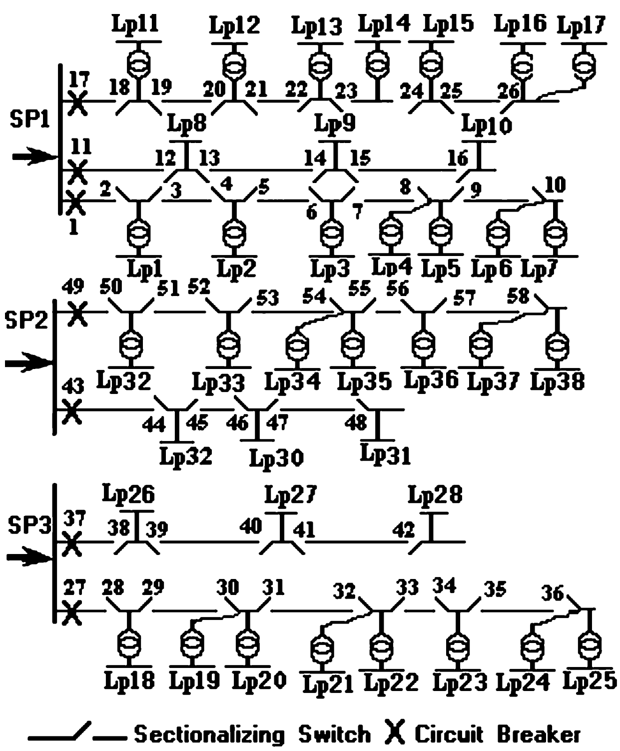

Fig. 7. Radial distribution network—test system I.

Step 9) total ECOST for contingency j is the sum of the three calculated ECOSTs in Steps 6)–8), then go to Step 1).

Fig. 6 shows the step-by-step switching intervals of the breaker, sectionalizers, and loop switch when a fault occurred between $S2$ and $S3$. A graph adjacency matrix is used to represent the distribution network topology in mathematical form. First, the depth search and breadth search algorithms are used to find power flow paths, sectionalizers, and breakers in these paths and to calculate ECOST for each set of switch locations.

VI. Case Studies and Numerical Results

The proposed algorithm is applied to two test systems shown in Figs. 7 and 8.

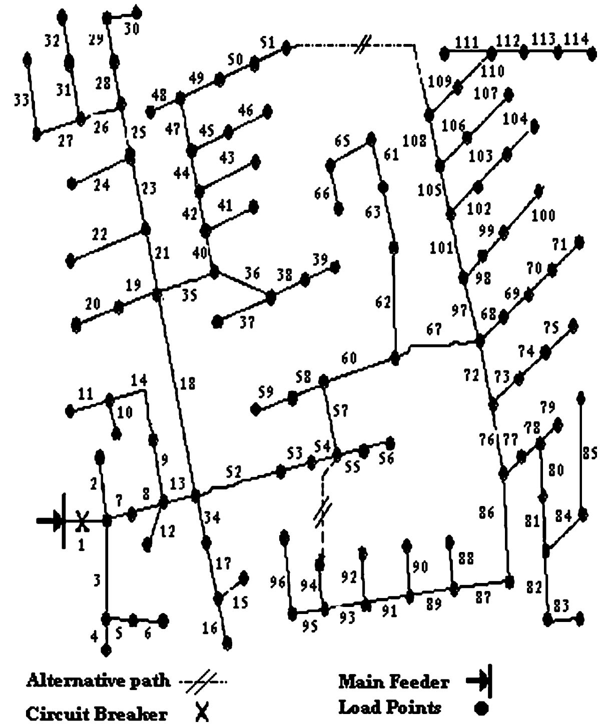

Fig. 8. IEEE 123-node feeder bus—test system II.

TABLE I
Optimal Location of Switches Using TPSO

Total Minimum Switching Device Cost	162028 ($/yr)
Number of Switches	12
Switch Locations	15, 29, 45, 55, 57, 4, 14, 26, 32, 40, 46, 58

A. Bus 4 of the RBTS

The first test system is a typical urban type configuration consisting of residential, industrial, commercial, and government/industrial customers. The peak load of the test system I is 40 MW and it is connected to bus 4 of the RBTS [13]. Customer data, equipment outage data, feeder loading, and customer interruption data are given in [13]. In this system, the investment costs of a sectionalizer and a breaker-type switch are U.S. $4700 and U.S. $11800, respectively [5]. The annual maintenance cost is 2% of the annual investment cost. As noted earlier, in addition to the investment cost, interruption cost is an important factor in determining the optimum number and locations of switches [5], [14].

The monetary values associated with customer damage cost have been taken from [5]. The life period of the switches is assumed to be 20 years with an interest rate of 8% [5]. There are 58 possible switch locations in the system. They are all shown in Fig. 7. The proposed algorithm is applied to this system and the results are shown in Table I. Since this system is a small and simple radial system, it is clear that the best locations for installing breakers are the main feeders. The results obtained from applying the proposed algorithm indicate that the best locations for installing breaker-type switches are the main feeders: 1, 11,

TABLE II
OPTIMAL LOCATIONS OF SWITCHES USING SA GIVEN IN [5]

Total Minimum Switching Device C	189033 ($/yr)
Number of Switches	14
Switch Locations	15, 31, 45, 53, 55, 57 10,14,26,36,40,42,48,52

17, 27, 37, 43, and 49, confirming good performance of the algorithm for this simple system.

The optimum number and locations of sectionalizers are also given in Table I. The results obtained by applying the simulated annealing (SA) algorithm to the same system are taken from [5] and shown in Table II. These results can be compared with Table I. It should be noted that in [5], only the best locations of sectionalizers are found and the locations of breakers are predetermined by default.

B. IEEE 123-Node Feeder Test System

The proposed algorithm is also applied to a more complex and practical system to examine the applicability of the algorithm in real circumstances.

The second test system is the IEEE 123-node feeder test system shown in Fig. 8. The system consists of 85 load points. There are 114 possible switch locations in this system. The required reliability data, including equipment outage data, feeder loading details, customer data, and load associated with each load point are given in [12].

Two different case studies are conducted in this section in order to determine the optimum number of switches (breakers and sectionalizers) and their locations using the proposed trinary PSO algorithm:

Case 1) without loop switches and alternative paths;
Case 2) with loop switches and alternative paths.

In the study results presented in this paper, it is assumed that a spare transformer is available for each individual transformer such that replacement time is considered in the case of a transformer failure. The following assumptions and modifications are applied to the IEEE 123-bus feeder.

1) All switches are assumed to have zero failure rates and, therefore, only independent failure modes associated with all transformers and transmission lines are considered in the analysis.
2) The system is supplied only from one 20-kV point and other normally open supplies are omitted. It contains both overhead transmission lines and underground cables.
3) Two alternative paths are considered in the system as shown in Fig. 8.
4) For each load point, one transformer is added to the original system.
5) Before applying a switch placement optimization algorithm, the main feeder breaker is assumed to be installed in the system (for the minimum level of protection).
6) Optimization algorithm is subjected to these constraints

$$V_i^{\min} < V_i < V_i^{\max}$$
$$I_i^{\min} < I_i < I_i^{\max}$$

TABLE III
FAILURE RATES AND REPAIR TIMES OF COMPONENTS

	Failure rate	Repair time (hr)
transformers	0.005 (f/yr)	Replacement time (10)
Transmission lines	0.065 (f/yr/km)	5

TABLE IV
TPSO PARAMETERS

C1	C2	C	Swarm Size	No. of Swarm Particles
2	2	2.9	114	50

where V_i and I_i are, respectively, the voltage and current of the ith load point. For the results presented in this paper $V_{\min}$ and $V_{\max}$ are, respectively, assumed to be 0.95 and 1.05 p.u.

7) In this system, the investment costs of a sectionalizer and a breaker-type switch are U.S. $4700 and U.S. $11800, respectively. The annual maintenance cost is 2% of the annual investment cost. The life period of the switches is assumed to be 20 years with an interest rate of 8% [5].
8) Switching time of RC sectionalizers (t_{sec}) and RC loop switches (t_{tie}) are assumed to be 5 min.
9) Repair time and failure rate of components are given in Table III and TPSO parameters are given in Table IV.
10) A section is a link between two load points. The numbers denoted in Fig. 8 are considered section numbers.
11) In this paper, it is assumed that sectionalizers are not fault-breaking switches and, therefore, any short circuit on a feeder causes the first breaker on the path from the fault location to the supply to operate. Sectionalizer switches are considered RC switch types. Once the fault has been detected, the relevant sectionalizer can be opened and the breaker reclosed. This procedure allows restoration of all load points between the supply point and the point of isolation before completing the repair process. Therefore, as the number of breaker type of switches are increased, fewer load points are disconnected and, as such, the total system ECOST decreases. Fig. 9 displays the convergence rate of the TPSO algorithm.

The algorithm is converged to its final state approximately after 50 iterations. The convergence rate of the algorithm with T_2 is more than with T_1. The reason for this is that this function is more symmetrical around midpoint and the chance of trapping in local minimum is less than the other function. For considering an economical analysis of the system, the system ECOST is calculated in four different cases and the results are given in Table V:

Case 1) before installing any switches in the system;
Case 2) after installing only breakers in all candidate positions;
Case 3) after installing only sectionalizers in all candidate positions;
Case 4) after installing switches by applying the proposed algorithm and determining optimum locations for installing sectionalizers and breakers.

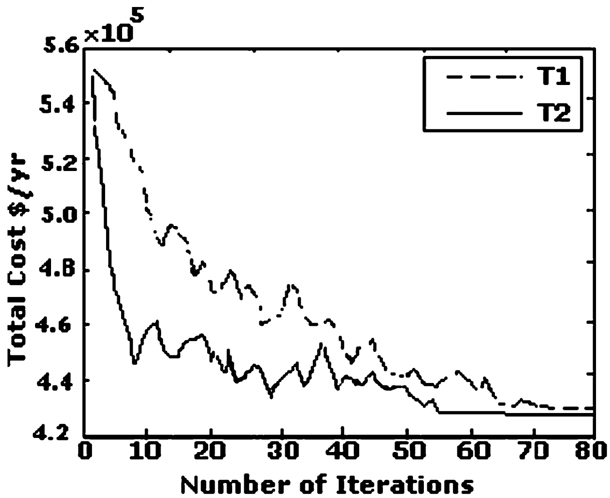

Fig. 9. Convergence rate of the proposed algorithm.

TABLE V
ECONOMICAL ANALYSIS OF CASE STUDY 1

	A	B	C	D
ECOST($)	430890	165700	287000	299300
Sw. Cost($)	-	219940	87600	43130
Total Cost($)	430890	385640	374600	342430

From Table V, it can be seen that installing an optimum number of switches in the optimum locations by applying the TPSO algorithm results in a reduction of system ECOST from U.S. $430 890 to U.S. $299 300/yr and the system total cost from U.S. $430 890/yr to U.S. $342 460/yr. To compare the present value of the future benefits by the investment cost of installing switches, discounted cash flow (DCF) analysis has been performed and the discounted future benefit (DFB) is calculated

$$\mathrm{DFB} = \sum_{t=0}^{20} \frac{(430890 - 299300)}{(1 + 0.08)^t} = 1423600\$$$

which is more than the investment and maintenance cost (U.S. $369 300). Therefore, installing switches in this system is a reasonable investment from an economical points of view.

The results for Cases 1) and 2) are presented in Tables VI and VII, respectively. It can be seen from the results that in the second case, the system reliability increases when loop switches are included. The reason for this is that isolated load points can be energized through alternative paths. The optimum number of switches in the second case is more than that of the first case. The reason for this is that effectiveness of loop switches is more dominant when the number of sectionalizer switches is adequate. For each faulted zone for using an alternative path, at least two loop switches are needed to isolate a faulty area from the network. The total cost of each sectionalizing and breaker switch is considered to be the same as the test system I. For the second case, the total cost of each alternative path is assumed to be equal as a sectionalizer cost.

Fig. 10 shows the proportional number of breakers and sectionalizers versus the proportional cost of one breaker and the cost of one sectionalizer. The results shown in this figure verify the performance of the proposed algorithm. The parameters represent switching times for RC sectionalizes. It can be seen from this figure that the required number of breakers decreases as the cost of a breaker-type switch is increased compared to that of a sectionalizer. Also, when the cost of a breaker is twice that of a sectionalizer, the number of breakers decreases compared to that of sectionalizers as the switching time for RC sectionalizes decreases. The reason for this is that when switching times for RC

TABLE VI
OPTIMUM LOCATIONS OF SWITCHES IN CASE STUDY 1

Number of breakers	12
Breakers locations	7,13,18,35,42,54,60,67,68,76 ,91,105
Number of Sectionalizers	26
Sectionalizer locations	1,3,8,9,21,25,26,36,40,49,50, 53,57,63,69,73,75,77,80,86,8 9,93,101,108,109,112
Switches Cost [$/yr]	43130
ECOST [$/yr]	299300
Total optimum cost	342430

TABLE VII
OPTIMUM LOCATIONS OF SWITCHES IN CASE STUDY II

Number of breakers	13
Breakers locations	7,9 ,40,47,97,62, 77,87,54,67,94,105,109
Number of Sectionalizers	29
Sectionalizer locations	1,3,8,13,14,21,25,26,35,36,42 ,45,52,53,55,57,63,68,73,78,8 0,86,89,91,93,99,101,110,112
Loop Switch	51-108, 94-54
Switches Cost [$/yr]	49350
ECOST [$/yr]	277500
Total optimum cost	326850

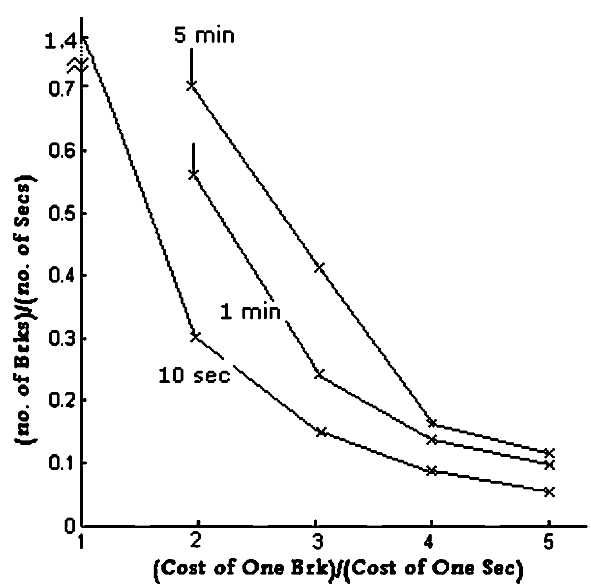

Fig. 10. m/n versus BRC /SEC.

sectionalizes are high, it implies that interrupted load points will be left disconnected for a longer time and, therefore, it is worthy to install a breaker-type switch rather than a sectionalizer. However, when the switching time for RC sectionalizes is short, interrupted load points are recovered in a short period of time resulting in less interruption cost. In this case, it is not worth it to install an expensive breaker-type switch compared to a cheaper sectionalizer. This can clearly be seen that if the cost of a breaker is the same as that of a sectionalizer, all of the switches obtained from the TPSO algorithm become a breaker-type switch when switching time for RC sectionalizes is more than 1 min (i.e., the number of sectionalizers becomes zero). It can therefore be concluded that for fixed costs of breakers and sectionalizers, the number of breaker-type switches increases as the switching time for RC sectionalizers increases.

VII. Conclusion

Determination of the optimum number and locations of switches in distribution system is an important issue from the reliability and economical points of view.

The switch placement problem is a combinatorial optimization problem with a nonlinear and nondifferential objective function. Using the idea of a history-based PSO algorithm and phasor concept in the plane, a novel three-state particle swarm optimization algorithm was formulated in this paper to determine the optimum number of two types of switches and their locations in a distribution system. The proposed approach designated as the TPSO algorithm, determines the optimum number/locations of switches by minimizing the total cost. The proposed approach has been applied to two test systems. The results presented indicate that the system reliability and cost are affected by the number and cost of breakers, number and cost of sectionalizers, their locations, and availability of alternative supplies.

References

[1] A. Moradi, M. Fotuhi-Firuzabad, and M. Rashidi-Nejad, "A reliability cost/worth approach to determine optimum switching placement in distribution systems," presented at the IEEE/Power Eng. Soc. Transmission and Distribution Conf. Exhibit.: Asia and Pacific, Dalian, China, 2005.

[2] J. F. Schutte, J. A. Reinbolt, B. J. Fregly, R. T. Haftka, and A. D. George, *Parallel Global Optimization With the Particle Swarm Algorithm*. New York: Wiley, 2004.

[3] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Networks*, Perth, Australia, 1995, vol. IV, pp. 1942–1948.

[4] B. E. Wells, C. Patrick, L. Trevino, J. Weir, and J. Steinca, "Applying particle swarm optimization to a discrete variable problem on an FPGA-based architecture," presented at the MAPLD Int. Conf., Washington, D.C., 2005.

[5] R. Billinton and S. Jonnavithula, "Optimal switching device placement in radial distribution systems," *IEEE Trans. Power Del.*, vol. 11, no. 3, pp. 1646–1651, Jul. 1996.

[6] J.-H. Teng and Y.-H. Liu, "A novel ACS-based optimum switch relocation method," *IEEE Trans. Power Syst.*, vol. 18, no. 1, pp. 113–120, Feb. 2003.

[7] P. M. S. Carvalho, L. A. F. M. Ferreira, and A. J. Cerejo da Silva, "A decomposition approach to optimal remote controlled switch allocation in distribution systems," *IEEE Trans. Power Del.*, vol. 20, no. 2, pt. 1, pp. 1031–1036, Apr. 2005.

[8] Z.-L. Gaing, "A particle swarm optimization approach for optimum design of PID controller in AVR system," *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 384–391, Jun. 2004.

[9] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment," *IEEE Trans. Power Syst.*, vol. 15, no. 4, pp. 1232–1239, Nov. 2000.

[10] A. A. Esmin, G. Lambert-Torres, and A. C. Zambroni de Souza, "A hybrid particle swarm optimization applied to loss power minimization," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 859–866, May 2005.

[11] J. Kennedy and R. C. Eberhart, "A discrete binary version of the particle swarm algorithm," in *Proc. Conf. Systems, Man, Cybernetics*, Piscataway, NJ, 1997, pp. 4104–4109.

[12] Power engineering society, power system analysis, computing and economics committee, distribution system analysis subcommittee, "IEEE 123 node test feeders," presented at the IEEE Winter Power Meeting, Columbus, OH, 2001.

[13] R. N. Billinton and I. Sjarief, "A reliability test system for educational purposes-basic distribution system data and results," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 813–820, May 1991.

[14] A. A. Chowdhury and D. O. Koval, "Value-based distribution system reliability planning," *IEEE Trans. Ind. Appl.*, vol. 34, no. 1, pp. 23–29, Jan./Feb. 1998.

Adel Moradi was born in Iran in 1981. He received the B.Sc. and M.Sc. degrees in electrical engineering from Sharif University of Technology, Tehran, Iran, in 2003 and 2005, respectively.

Currently, he is a Research Assistant in the Laboratory for Power Systems, Sharif University of Technology, where his research interests include the design and control of miniaturized power converters, hybrid vehicular systems, and distribution system reliability enhancement using automation.

M. Fotuhi-Firuzabad (SM'99) was born in Iran. He received the B.Sc. and M.Sc. degrees in electrical engineering from Sharif University of Technology, Tehran, Iran, and Tehran University, Tehran, in 1986 and 1989, respectively, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Saskatchewan, Saskatoon, SK, Canada, in 1993 and 1997, respectively.

He was a Postdoctoral Fellow in the Department of Electrical Engineering, University of Saskatchewan, from 1998 to 2000 and from 2001 to 2002, where he conducted research in the area of power system reliability. He was an Assistant Professor in the same department from 2000 to 2001. Currently, he is an Associate Professor and Head of the Department of Electrical Engineering, Sharif University of Technology.

Dr. Fotuhi-Firuzabad is a member of Center of Excellence in Power System Control and Management in the Electrical Engineering Department.