High Order Contingency Selection Using Particle Swarm Optimization and Tabu Search

Fangxing Li, *Senior Member, IEEE* and Ashwini Chegu, *Student Member, IEEE*

***Abstract*— There is a growing interest in investigating the high order contingency events that may result in large blackouts, which have been a great concern for power grid secure operation. The actual number of high order contingency is too large for operators and planner to apply a brute-force enumerative analysis. This paper presents a method, which combines the unique features of particle swarm optimization (PSO) and tabu search, to select severe high order contingencies. The original PSO algorithm gives an intelligent strategy to search the feasible solution space, but tends to find the best solution only. The proposed method combines the original PSO with tabu search such that a number of top candidates will be identified. This fits the need of high order contingency screening, which can be eventually the input to many other more complicate security analyses.**

Keywords - blackouts; high order contingency; N-k contingency; particle swarm optimization; tabu search.

I. INTRODUCTION

THERE is an increasing concern of high order contingency events in power system operation that may lead to a large scale blackout. Literally, high order contingency or N-k contingency means multiple component failures that coincidently occur near simultaneously [1-4]. Although there is an argument that a blackout occurs mainly due to a cascading failure following a single initial triggering event and failures are "correlated" [5-10], it is still important to analyze high order contingency because of two reasons. First, the initial triggering event may be a simultaneous, high-order contingency. Second, the first a few lines are sequentially tripped due to a single initial contingency may occur so closely that they can be treated as near simultaneously. In recent years, this has been a particular concern for power transmission operators as evidenced by many researches in high order contingency analysis as well as the utility practices. For instance, many power transmission operators have expanded contingency criterion from N-1 only to N-1 and some N-2 and even N-3 contingencies.

High order contingency events are difficult to analyze and model. If we take possible combinations of N-k contingency, then the total number of possible combination is N!/[k!×(N-k)!], which is as huge as 499,500 for a relatively small system with N=1000 and k=2. And the number of cases are much worsened to 166,167,000 if k=3. Hence, brute-force enumeration is not likely an efficient approach especially for short term operations. Therefore, there is a need for efficient high order contingency screening approach, especially considering potential short-term operation.

This paper presents a method, which combines the unique features of particle swarm optimization (PSO) and tabu search, to select a subset of severe high order contingencies. The original PSO algorithm gives an intelligent strategy to search the feasible solution space, but tends to find the best solution only. The proposed method combines the original PSO with tabu search such that a number of top candidates will be identified. This fits the need of high order contingency screening, which can be eventually the input to many other more complicate security analyses.

II. PROPOSED METHOD

This section first reviews the original version of a common formulation of particle swarm optimization. Then, application to high order analysis is discussed. Last, tabu search is combined to find a set of severe high order contingency events.

A. Particle Swarm Optimization

Particle swarm optimization technique [11] was introduced by Kennedy and Eberhart in 1995. It is a population based method for function optimization where swarm of individuals also called particles, explores the whole search space. It can be used to solve complex optimization problems which are non-linear, non-differentiable, and multimodal. The method is more advantageous for its fast convergence speed and can be realized only by adjusting few parameters. PSO can be applied to various power system optimization problems with impressive success.

PSO can be viewed as an analogy of a flock of bees to search for the best location of flowers (i.e., highest flower density). Each individual bee may start at a random location in the given field, and they should move around following some rules to find the best location of flowers. Also assumed is that they can communicate freely. Then, the next move of each bee will be impacted by its personal best, P_{best}, for all locations that this particular bee has visit, as well as the global best, G_{best}, that all bees have visited. After each bee visits a new location, P_{best} and G_{best} will be updated such that the "next-next" move will be further updated to formulate an iterative solution. Therefore, all bees will eventually concentrate on the same location which is the expected true global best. This is shown in Fig. 1.

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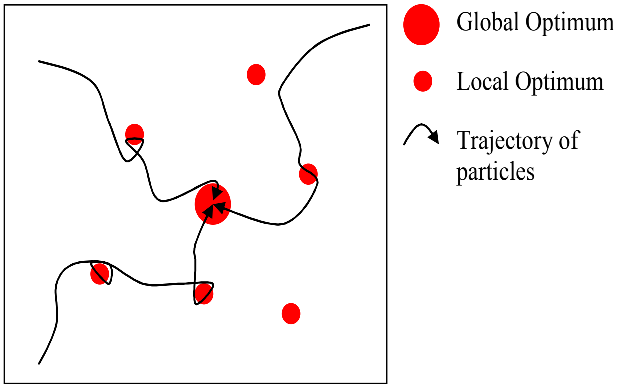

Fig. 1. Illustration of PSO technique.

B. PSO for High Order Contingency Selection

In this paper the PSO technique is applied to assist with searching the space of possible high order contingency events. The basic idea is described below with an example of N-2 contingencies that are easier to visualize and explain in a two-dimensional diagram.

The searching space consists of x and y as independent variables, and z as the fitness function. Here, x and y stand for the branch IDs that are subject to contingency. For instance, if we have (x, y, z) =(5,9, 300), then it means that after Branch 5 and Branch 9 are removed from the system, the fitness function (i.e., the impact) is 300. Certainly, there may be various ways to define the fitness function. In this paper, we define the fitness function as follows:

$$z(x, y) = \sum_{k \in \{OL\}} \left| \frac{P_k}{P_k^{\max}} \right| \tag{1}$$

where {OL}= the set of overloaded lines after removing Branches x and y.

Equation (1) is calculated based on N-2 contingency power flow; therefore, it is essentially an indication of how severe the N-2 contingency could be. It should be noted that here no possible control action is considered; although in reality some certain control action may be possible. Hence, the post-contingency power flow can be viewed as a conservative evaluation of the fitness function (i.e., the impact) of N-2 contingency. However, as long as the impact from every possible N-2 contingency is evaluated under the same conservative viewpoint, the fitness function defined in (1) should be a fair representation of severity.

Next, the swarm consists of a few particles initially chosen randomly in a two dimensional diagram. For each particle within each iteration, it flies through the search space based on the velocity vector calculated based on its momentum and the influence of its best solution and the best solution of its neighbors. Although there are many variants of PSO techniques, here we choose the new location of particle and the new velocity given by the following two equations, respectively.

$$S_{i+1} = S_i + V_{i+1} \tag{2}$$

$$V_{i+1} = w \times V_i + c_1 \times r_1 \times \left(P_i^{best} - S_i\right) + c_2 \times r_2 \times \left(G^{best} - S_i\right) \tag{3}$$

where
S_{i+1}= new x and y locations of the particle;
S_i= previous x and y locations of the particle;
V_{i+1}= the new velocity of the particle;
w = inertial weight;
r_1, r_2 = two random numbers in [0, 1] uniformly distributed;
c_1 = cognition component;
c_2 = social component.

The particles have memory and each particle keeps track of previous best position, p_{best} and corresponding fitness. Another value g_{best} is the best value of all the particles. Fitness evaluated is compared with the population's overall previous best. If the current value is better than g_{best}, then g_{best} is reset to the current particle's array value. Each particle is accelerated towards the combination of its p_{best} and the g_{best} locations at each iteration.

The original PSO algorithm attempts to find the best solution. Hence, only p_{best} and g_{best} are needed to be saved temporarily during the search. This does not meet the need of contingency selection in which a subset of all N-2 contingency events is desired. Therefore, we can use tabu search technique such that we have a list of the top *m*, which could be 100 or 1000 depending on the actual system, among all visited N-2 contingency events. After every iteration, the tabu list should be updated as long as there are some new locations visited by particles that are better than any existing items in the tabu list. Hence, when the algorithm converges, we have a list of top candidate N-2 contingency events.

Therefore, the principal of the proposed idea can be summarized as follows:

- The PSO algorithm is used to guide all particles to traverse through possible good candidate locations (here, "good" really means N-2 contingency with a high impact on line flows).
- The tabu search is applied to keep track of all "good" candidates.
- When PSO stops, it means that particles have visited all possible "good" candidate locations.

Based on Equation (2) and (3), it is easy to conclude that the convergence speed of the proposed algorithm depends on the choice of c_1 and c_2, the cognition and social coefficients, respectively. If c_1 is more dominant, the impact from the global best will have less impact on the future location of particles. Hence, the algorithm will traverse more spaces and take longer time to converge. In contrast, if c_2 is more dominant, then the particles are quickly attracted to the global best. Hence, convergence may be faster; however, this may means that the searching algorithm may miss some potential good candidates.

There are a few points regarding implementation that are worthwhile to mention:

- Since (x,y) represents the N-2 contingency losing Branch x and Branch y simultaneously, the order of x and y does not affect the fitness function defined in (1). Hence, the location (x, y) implies no difference than (y, x). Therefore, we can only utilize half of the entire searching space by automatically converting (y, x) to (x, y) if y>x. This means only the lower triangle shown in Fig. 2 is needed to reduce the computing time.
- If we have x=y for a particle after a new iteration using (3) and (4), we simply keep the previous location as the new one since only N-2 contingency is considered.
- If we have x or y out of bound, then we can set it to the boundary point, as shown in Fig. 3.

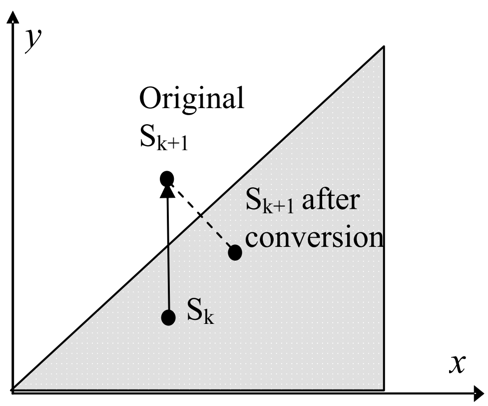

Fig. 2. Converting (x, y) to (y, x) due to symmetry of the fitness function *z(x,y)*.

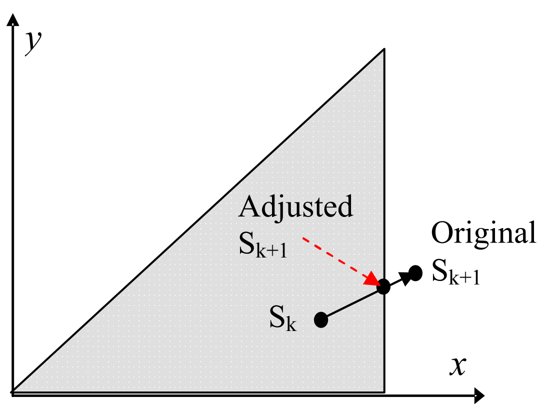

Fig. 3. Adjustment of an out-of-boundary case.

The overall flow chart of the proposed algorithm is illustrated in Fig. 4 below.

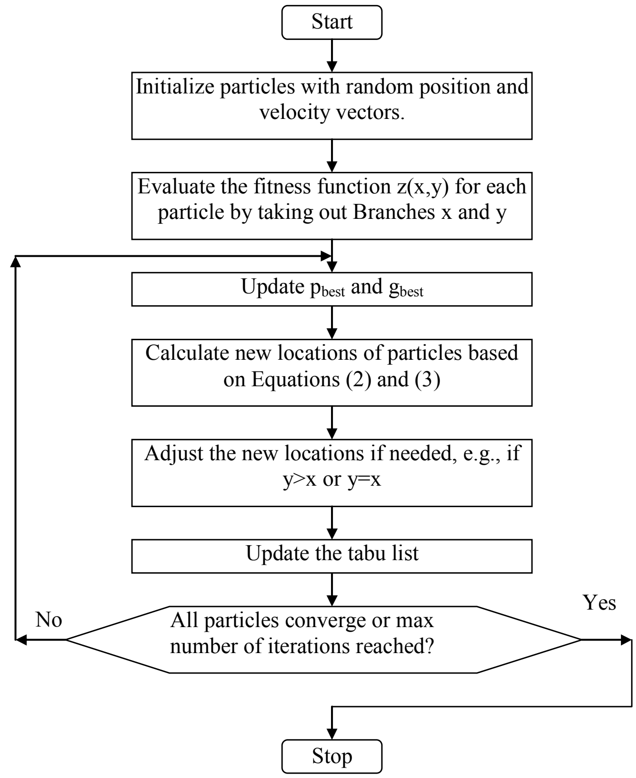

Fig. 4. Flow chart of the proposed method.

As previously mentioned, although the above discussion and illustration as well as the following tests are based on N-2 contingencies, it can be easily applied to higher order contingencies.

III. Concluding Remarks

This paper presents a method, which combines the unique features of particle swarm optimization (PSO) and tabu search, to select severe high order contingencies. The original PSO algorithm gives an intelligent strategy to search the feasible solution space, but tends to find the best solution only. The proposed method combines the original PSO with tabu search such that a number of top candidates will be identified. This fits the need of high order contingency screening, which can be eventually the input to many other more complicate security analyses.

Upon the completion of this paper, tests are undergone for the IEEE 300-bus system. Simulation results will be reported in the near future.

Also, further work may include the evaluation of the impact to speed and efficiency if different coefficients in (3) are applied. Also, different fitness function considering possible corrective actions under high order contingency events may be applied.

IV. References

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V. Biographies

Fangxing (Fran) Li (M'01, SM'05) received the Ph.D. degree from Virginia Tech in 2001. He has been an Assistant Professor at The University of Tennessee (UT), Knoxville, TN, USA, since August 2005. Prior to joining UT, he worked at ABB, Raleigh, NC, as a senior and then a principal R&D engineer for four and a half years. His current interests include energy market, reactive power, distributed energy resources, and infrastructure security. Dr. Li is a registered Professional Engineer (P.E.) in the state of North Carolina.

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