Research Article

Ant Colony Search Algorithm for Optimal Generators Startup during Power System Restoration

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Generators startup sequence plays a significant role in achieving a suitable and effective restoration strategy. This paper outlines an ant colony search algorithm in order to determine the generator starting times during the bulk power system restoration. The algorithm attempts to maximize the system generation capability over a restoration period, where the dynamic characteristics of different types of units and system constraints are considered. Applying this method for the 39-bus New England test system, and comparing the results with backtracking-search and P/t methods, it is found that proposed algorithm improved generation capability.

1. Introduction

In recent years, power systems are operated fairly close to their limits primarily due to economic competition and deregulation. At the same time, they have increased in size and complexity. Both factors increase the risk of major power outages [1]. After a blackout, power needs to be restored as quickly and reliably as possible, and consequently detailed restoration plans are necessary [2, 3]. While most restoration plans have been developed on a trial-and-error principle, there is a tendency to employ a more systematic planning and analysis of restoration procedures [4–10].

In the case of a total system outage, system restoration must begin from the black-start unit(s). Black-start units are units that do not require off-site power to start, such as: diesel generator sets and hydroelectric units [5]. As the Black-start units themselves can only supply a small fraction of the system load, these units must be used to assist in the starting of larger units, which need their station service loads to be supplied by outside

Table 1: Startup characteristics of different types of units.

Unit type	Crank power	Critical maximum interval	Critical minimum interval
Black-start (CT or Hydro)	No	No	No
Drum	Yes	Yes	No
SCOT	Yes	No	Yes

power sources. Full restoration of system load can only occur when these larger units can come on line. In order to achieve a suitable and effective restoration strategy, deciding on the generators startup sequence is an important task [7–10]. It should be pointed out that a proper sequence of generators start-up can increase the system MW outputs and keep the constraints satisfied. Optimal generators start-up strategy in system restoration is a multistage decision optimization problem.

A number of studies have been carried out to determine generators start-up sequence [7–10] using heuristic methods which do not guarantee their optimality. In this paper, from the global optimization point of view, a novel approach based on the Ant Colony Search (ACS) algorithm is proposed.

The goal of the proposed method is to maximize the total system generation capability over a restoration period whilst considering the corresponding static and dynamic constraints including the cranking power, critical maximum interval, and critical minimum interval constraints.

In the following sections, first the problem formulation is presented. The proposed ACS algorithm is then described. Finally, the simulation results for a 39-bus New England test system are illustrated and compared with those obtained by backtracking search and p/t methods.

2. Problem Formulation

During total blackout, the initial power source to crank non-black-start generators must be found. The initial source of power is provided by starting black-start generator quickly. For non-black-start generators, different physical characteristics and the starting requirements in each power station need to be considered. Table 1 shows startup characteristics of different types of units [7]. If a unit with a critical maximum interval is not started within the interval, there may be a delay of hours before the unit becomes available again. A unit with a critical minimum interval cannot be started until the interval ends. Hence, consideration of unit's constraints is essential for start-up sequence planning.

Figure 1 shows start up timing for a typical unit [11], where we have

t_0: restartup time,

t_1: synchronization time,

t_2-t_1: time to reach minimum load,

t_3-t_2: time to reach maximum load.

Finding proper cranking priorities for non-black-start units can increase the system MW output. The goal is to maximize G, the total system generation capability in MWH, which
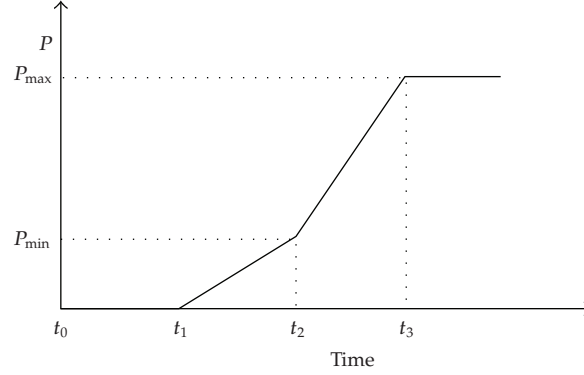
Figure 1: Startup timing for a typical unit.

can be produced during the restoration period as described below:

$$G = \sum_{i=1}^{n} \int_{t_i}^{T} P_i(t - t_i)dt, \tag{2.1}$$

where t_i is the start time for the ith generating unit whose generating capability is $P_i(t - t_i)$; T is the planning ending time.

The constraints to be considered in this problem are as follows:

(a) maximum MW output of units,

(b) reactive power over and under excitation limits (from generator capability curve),

(c) start-up times,

(d) start-up and house-load MW requirement,

(e) ramping rates.

To deliver cranking power from black-start to non-black-start units, it is necessary to build transmission paths between them. The number of required switching as well as limitations of the units MVAR are the two most important issues in path selection. Wherever units MVAR limitations permit, the shortest path (i.e., the path requiring the minimal number of switching action) between the supplying unit and the non-black-start unit is selected. A heuristic algorithm, called A^* search [12], is used to identify the shortest path. This algorithm also examines sum of line charging for the selected path as a constraint. This must be smaller than the limit MVAR absorbing capabilities of generating units.

Load restoration and power supply must coincide with each other to guarantee the stability of system frequency and voltage, because the restoration of power plants and that of loads are synchronous.

3. Ant Colony System Algorithm

Ant Colony Optimization (ACO) method handles successfully various combinatorial complex problems. Dorigo, inspired by the behavior of real ant colonies, proposed ACO
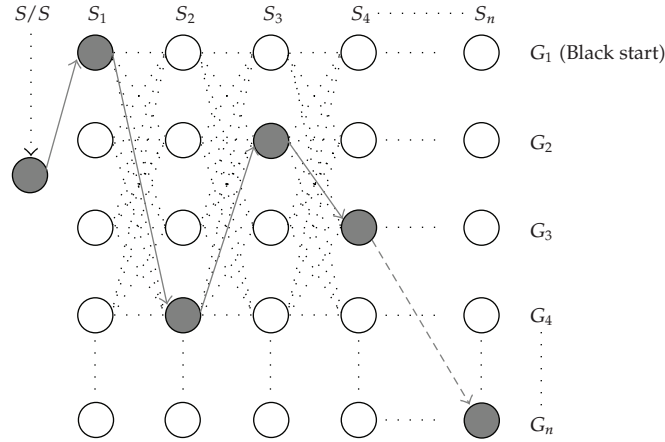
Figure 2: Search space of ant sequence determination.

method for the first time in his Ph. D. thesis [13]. The method is postulated on the basis of a set of artificial ants which cooperate in solving a problem by exchanging information via pheromone deposited on a graph. It can be used to solve both continuous and discontinuous, nonconvex, nonlinear constrained optimization problems. The characteristics of ACO include positive feedback, distributed computation, and utilization of constructive greedy heuristic.

Recently a large number of different ACO algorithms have become available. All of these algorithms contain a strong exploitation of the best solutions found during the search; the most successful of which add explicit features to the search in order to avoid premature stagnation. The main differences between the various ant system extensions consist of the techniques used to control the search process. ACS is reported to be the most aggressive of the ACO algorithms [13] returning the best solution quality for very short computation times.

In power systems, the ACO has been applied to solve the optimum generation scheduling problems [14], unit commitment [15], economic dispatch [16], and the constrained load flow [17].

Once the search space of generators start-up problem is established using multi-process decision making concept, the ACS algorithm can be applied to problems such as traveling salesman problem (TSP). TSP defines the task of finding a tour of minimal total cost given a set of fully connected nodes and costs associated with each pair of nodes. The tour must be closed and contain each node exactly once. This can be represented as a sequence of n items, where the actual order of the sequence determines a particular solution to the problem. Thus, in general, the search space consists of all $n!$ permutations.

The sequence in which generators are started up during system restoration is important since different sequences yield different MWH outputs. Figure 2 shows the search space of ant sequence determination where the first generator is a black-start unit. For the kth sequence (S_k), the generator will be started up at t_{S_k}; the exact time of which depends on the system condition and the generator start-up MW requirement. The cost function for sequence S is

$$C(S) = \sum_{i=1}^{n} TC(S_{i-1}, S_i),\qquad(3.1)$$

where $TC(S_{i-1}, S_i)$ is the transition cost between the sequence $(i-1)$ and i, defined as follows:

$$TC(S_{i-1}, S_i) = -\int_{t_{S_i}}^{T} (P_{S_i} - Pcr_{S_i}) \cdot dt, \tag{3.2}$$

where t_{S_i}, P_{S_i}, and Pcr_{S_i} are starting time, MW output, and cranking power of generator at ith sequence, respectively. It should be noted that the cost function C in (3.1) is in fact equal to G in quantity at (2.1) but with negative sign and C should, therefore, be minimized.

The two main phases of the ACS algorithm constitute the ants' solution construction and the pheromone update.

In this algorithm, ants find solutions starting from a start node and move to feasible neighbor nodes in the process of ants' generation and activity. During the process, information collected by ants is stored in the so-called pheromone trails. During the process, ants can also release pheromone while building the solution (local pheromone trail update) or after the solution is built (global pheromone trail update). An ant-decision rule, made up of the pheromone and heuristic information, governs ants' search toward neighbor nodes stochastically. Pheromone evaporation is a process of decreasing the intensities of pheromone trails over time. This process is used to avoid local convergence and explore more search areas.

3.1. Sequence Construction

Sequences are constructed by applying the following simple constructive procedure to each ant: (1) choose a start unit (black-start unit) at which the ant is positioned; (2) use pheromone and heuristic values to construct a sequence on probability basis, by iteratively adding units that the ant has not yet visited. This will continue until all units have been visited. In ACS, when located at unit i, ant k moves to a unit j chosen according to the so called pseudorandom proportional rule, given by

$$j = \begin{cases} \arg \left\{ \max\limits_{u \in S_k} \left[\tau_{iu} \cdot (\eta_{iu})^{\beta} \right] \right\} & \text{if } (q \leq q_0), \\ J & \text{otherwise,} \end{cases} \tag{3.3}$$

where τ_{iu} is the pheromone trail, $\eta_{iu} = 1/tc_{iu}$ is the problem-specific heuristic information, and β is a parameter representing the importance of heuristic information, q is a random number uniformly distributed in $[0, 1]$, q_0 is a prespecified parameter $(0 \leq q_0 \leq 1)$ and $(1 - q_0)$ can be interpreted as trail evaporation, S_k is the set of units currently not passed by ant k, and J is a random variable selected according to the probability distribution given by

$$P_{ij}^k = \begin{cases} \dfrac{(\tau_{ij})(\eta_{ij})^{\beta}}{\sum_{u \in S_k} (\tau_{iu})(\eta_{iu})^{\beta}} & \text{if } j \in S_k, \\ 0 & \text{otherwise.} \end{cases} \tag{3.4}$$

In other words, with probability q_0 the ant makes the best possible move as indicated by the learned pheromone trails and the heuristic information (in this case, the ant is exploiting the learned knowledge), while with probability $(1 - q_0)$ it performs a biased exploration of the arcs. Tuning the parameter q_0 allows modulation of the degree of exploration and the choice of whether to concentrate the search of the system around the best-so-far solution or to explore other sequences.

3.2. Global Pheromone Trail Update

In ACS, following each iteration, only one ant (the best-so-far ant) is allowed to add pheromone such that the new pheromone trail becomes a weighted average between the old pheromone value and the amount of pheromone deposited. Thus, the update in ACS is implemented by the following equation:

$$\tau_{ij} \longleftarrow (1 - \rho)\tau_{ij} + \rho \Delta \tau_{ij}^{bs} \quad \forall (i,j) \in S^{bs}, \tag{3.5}$$

where (i,j)'s are the edges belonging to S^{bs}, the best minimum cost sequence since the beginning of the trial, $0 < \rho < 1$ is a parameter governing global pheromone decay, and change in pheromone is given by

$$\Delta \tau_{ij}^{bs} = \frac{1}{C^{bs}}, \tag{3.6}$$

where C^{bs} is the best-so-far cost. It is important to note that in ACS the pheromone trail update, both evaporation and new pheromone deposit, only applies to the best sequence.

3.3. Local Pheromone Trail Update

In addition to the global pheromone trail updating rule, in ACS the ants use a local pheromone update rule that they apply immediately after having crossed a sequence (i,j) during the sequence construction:

$$\tau_{ij} \longleftarrow (1 - \xi)\tau_{ij} + \xi \tau_0, \tag{3.7}$$

where $0 < \xi < 1$ is a constant governing the local pheromone decay process and τ_0 is the initial value of the pheromone trails. The effect of the local updating rule is that each time an ant uses a sequence (i,j) its pheromone trail τ_{ij} is reduced, so that the sequence becomes less desirable for the following ants. In other words, ants do not converge to the generation of a common sequence.

The flowchart of the ACS algorithm for optimal generators start-up is shown in Figure 3.

```
                    ┌───────────┐
                    │   Start   │
                    └───────────┘
                          │
                          ▼
              ┌───────────────────────┐
              │ Input units start-up  │
              │    characteristics    │
              └───────────────────────┘
                          │
                          ▼
              ┌───────────────────────┐
              │ Initialization and    │
              │ parameters            │
              │ selection for the ACS │
              └───────────────────────┘
                          │
                          ▼
              ┌───────────────────────┐
              │ Iteration counter i=1 │
              └───────────────────────┘
```
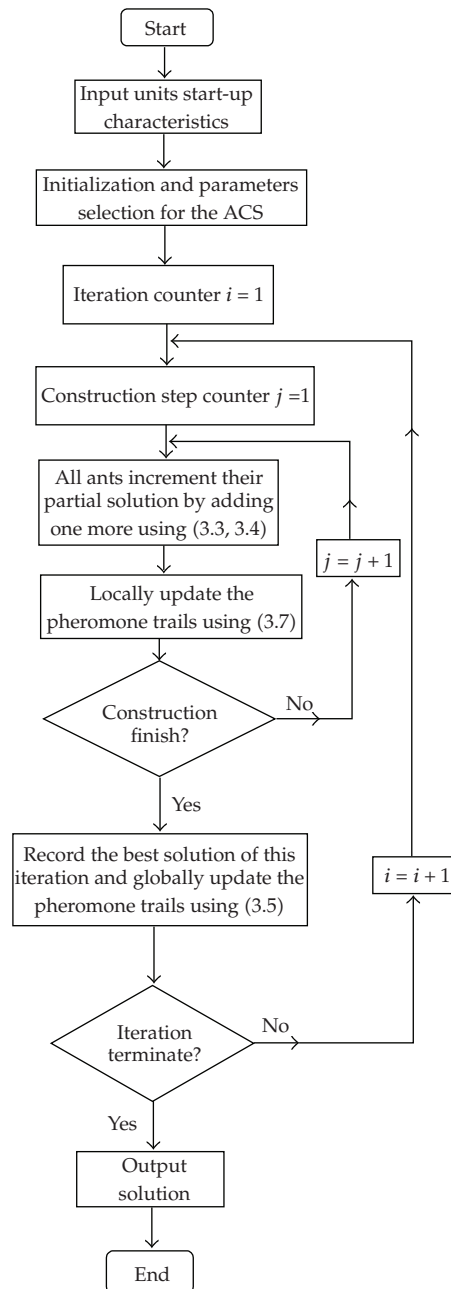
Figure 3: The flowchart of the ACS algorithm for optimal generators start-up.

3.4. Parameter Settings

Good convergence behavior of ACS algorithm can be achieved by suitable selection of parameters. The parameters that affect the computation of ACS algorithm directly or indirectly include ant number, ρ, ξ, β, and q_0.
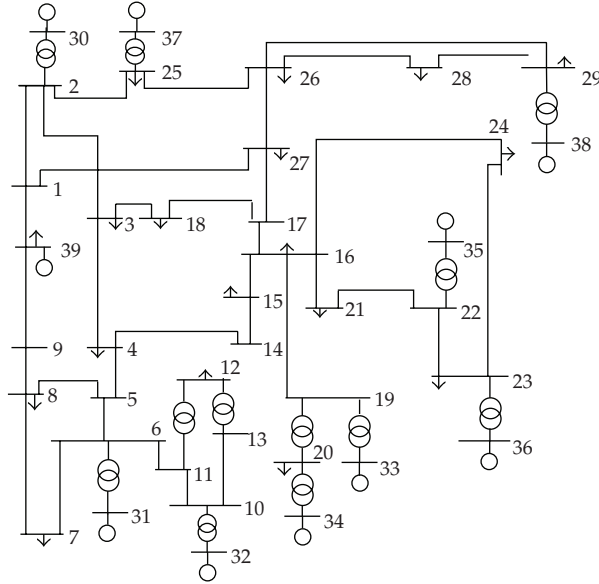
Figure 4: One line diagram of 39 bus New England test system.

The settings are done for 39-bus New England system whose characteristics are given in next section. They are tested for each parameter taking several values within a boundary limit, all others being constant. More than 10 simulations for each setting are performed in order to achieve some statistical information about the average evolution. The range of interval considered for each parameters are $\rho\{0.1\ 0.9\}$, $\xi\{0.1\ 0.9\}$, $\beta\{0\ 10\}$, and $q_0\{0\ 1\}$.

The initial trail level is set as $\tau_0 = 1$. The number of ants allowed to pass through the search space is taken as the generators' number. The final combination of parameters (ρ, ξ, β, q_0) that provided the best results is (0.1, 0.1, 2, 0.98).

4. Case Study

In this section, the proposed method is used for restoration of 39-bus New England system (see Figure 4). The system includes 39 buses, 10 generators, 35 lines, and 12 transformers, and generators in buses 30 and 35 are black-start units, and thus there are 2 subsystems (islands) for simultaneous restoration.

The results of proposed method are compared with results of P/t and backtracking search method. In P/t method, the priority for generators start-up is determined based on the ratio of MW capability and the time required for the plant to be synchronized with the system, whose, the generator that its P/t is greater than others has priority for start-up [7]. Backtracking search method determines problem solutions by systematically searching the solution space using a tree organization [9].

Figure 5 shows the performances of ACS algorithm during starting sequence optimization.

Tables 2, 3, and 4 show the results of generators start-up sequence using the proposed method, backtracking search method, and P/t method, respectively.
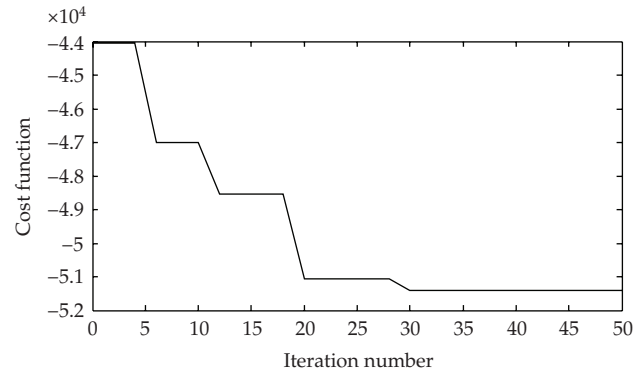
Figure 5: Performances of ACS algorithm during starting sequence optimization.

Proposed method
Backtracking method
P/t method
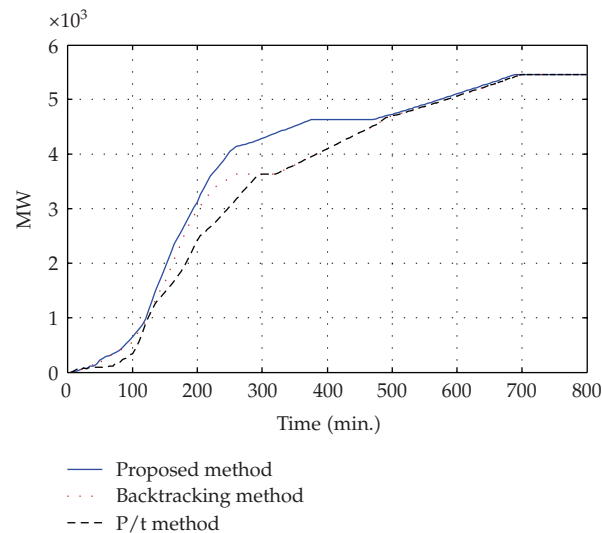
Figure 6: Generation capability of 39-bus New England system.

Figure 6 shows generation capability of the system after system restoration for the three generators start-up sequences.

During the first 800 minutes of system restoration, the system generation capability for the proposed method, backtracking search method, and P/t method are 51402, 48535, and 46946 MWH, respectively. This indicates that determination of optimal sequence for start-up can increase generation capability of the system during system restoration.

These simulation results and other test cases show the improved effectiveness and accuracy of the proposed method in identifying the optimal generator's start-up sequence.

During restoration of large power system, it is advantageous in most cases to split the power system into subsystems in order to allow parallel restoration of islands, and to reduce the overall restoration time. Within each subsystem, the proposed method can be used to determine optimal starting sequence. Then the subsystems are interconnected and remaining loads are picked up and the system performs its transition to the normal state.

Table 2: Generator start-up sequence and selected path with the proposed method.

Unit no.	Bus no.	Cranking unit	Start time	Selected path for energization
1	30	Black start	0 : 00	—
6	35	Black start	0 : 00	—
4	33	6	0 : 10	(35-22), (22-21), (21-16), (16-19), (19-33)
10	39	1	0 : 15	(30-2), (2-1), (1-39)
7	36	6	0 : 20	(22-23), (23-36)
2	31	6	0 : 30	(16-15), (15-14), (14-4), (4-5), (5-6), (6-31)
3	32	4	0 : 40	(33-19), (14-13), (13-10), (10-32)
5	34	4	0 : 45	(19-20), (20-34)
8	37	10	2 : 00	(2-25), (25-37)
9	38	10	3 : 20	(1-27), (27-26), (26-29), (29-38)

Table 3: Generator start-up sequence and selected path with the backtracking search method.

Unit no.	Bus no.	Cranking unit	Start time	Selected path for energization
1	30	Black start	0 : 00	—
6	35	Black start	0 : 00	—
4	33	6	0 : 10	(35-22), (22-21), (21-16), (16-19), (19-33)
7	36	6	0 : 20	(35-22), (22-23), (23-36)
8	37	1	0 : 20	(30-2), (2-25), (25-37)
5	34	4	0 : 40	(19-20), (20-34)
3	32	4	0 : 50	(16-15), (15-14), (14-13), (13-10), (10-32)
2	31	4	0 : 50	(10-11), (11-6), (6-31)
10	39	8	1 : 40	(2-1), (1-39)
9	38	8	3 : 30	(25-26), (26-29), (29-38)

Table 4: Generator start-up sequence and selected path with the P/T method.

Unit no.	Bus no.	Cranking unit	Start time	Selected path for energization
1	30	Black start	0 : 00	—
6	35	Black start	0 : 00	—
7	36	6	0 : 20	(35-22), (22-23), (23-36)
8	37	1	0 : 20	(30-2), (2-25), (25-37)
5	34	6	0 : 30	(22-21), (21-16), (16-19), (19-20), (20-34)
4	33	7	1 : 10	(19-33)
2	31	7	1 : 10	(16-15), (15-14), (14-4), (4-5), (5-6), (6-32)
3	32	7	1 : 20	(14-13), (13-10), (10-32)
10	39	8	1 : 40	(2-1), (1-39)
9	38	8	3 : 30	(25-26), (26-29), (29-38)

5. Conclusion

A method for unit start-up sequence determination during system restoration is described in this article. Once the search space of generators start-up problem is established using multiprocess decision-making concept, the ACS algorithm is used to determine the units starting times to maximize the generation capability dispatch during restoration period. The dynamic characteristics of different types of units and system constraints are also considered. The proposed method has been tested on the 39-bus New England test system in order to determine the optimal start-up sequence. The results are then compared with those obtained by the backtracking search method and P/t method, which indicated improved effectiveness and accuracy of the proposed method.

References

[1] G. Andersson, P. Donalek, R. Farmer, et al., "Causes of the 2003 major grid blackouts in North America Europe, and recommended means to improve system dynamic performance," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1922–1928, 2005.

[2] M. M. Adibi and L. H. Fink, "Power system restoration planning," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 22–28, 1994.

[3] J. J. Ancona, "Framework for power system restoration following a major power failure," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1480–1485, 1995.

[4] Y. Kojima, S. Warashina, M. Kato, and H. Watanabe, "Application of knowledge engineering techniques to electric power system restoration," in *Proceedings of IEEE Workshop on Artificial Intelligence for Industrial Applications*, pp. 320–325, 1988.

[5] M. M. Adibi, T. L. Volkmann, and M. Northern, "Remote cranking of steam electric stations," *IEEE Transactions on Power Systems*, vol. 11, no. 3, pp. 1613–1618, 1996.

[6] F. P. de Mello and J. C. Westcott, "Steam plant startup and control in system restoration," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 93–101, 1994.

[7] C.-C. Liu, K.-L. Liou, R. F. Chu, and A. T. Holen, "Generation capability dispatch for bulk power system restoration. A knowledge-based approach," *IEEE Transactions on Power Systems*, vol. 8, no. 1, pp. 316–325, 1993.

[8] T. Nagata, H. Sasaki, and R. Yokoyama, "Power system restoration by joint usage of expert system and mathematical programming approach," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1473–1479, 1995.

[9] A. Ketabi, H. Asmar, A. M. Ranjbar, and R. Feuillet, "An approach for optimal units start-up during bulk power system restoration," in *Proceedings of the Large Engineering Systems Conference on Power Engineering*, pp. 190–194, 2001.

[10] Y. Liu and X. Gu, "Skeleton-network reconfiguration based on topological characteristics of scale-free networks and discrete particle swarm optimization," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1267–1274, 2007.

[11] British Electricity International, *Modern Power Station Practice*, vol. C, D, and G, Pergamon Press, Oxford, UK, 1991.

[12] S. L. Tanimoto, *The Elements of Artificial Intelligence: An Introduction Using LISP*, Computer Science Press, New York, NY, USA, 1987.

[13] M. Dorigo and T. Stützle, *Ant Colony Optimization*, MIT Press, Cambridge, Mass, USA, 2004.

[14] Y. U. In-Keun, C. S. Chou, and Y. H. Song, "Application of the ant colony search algorithm to short-term generation scheduling problem of thermal units," in *Proceedings of the International Conference on Power System Technology*, vol. 1, pp. 552–556, 1998.

[15] M. Y. El-Sharkh, N. S. Sisworahardjo, A. Rahman, and M. S. Alam, "An improved ant colony search algorithm for unit commitment application," in *Proceedings of IEEE Power Systems Conference and Exposition*, pp. 1741–1746, 2006.

[16] Y. H. Hou, Y. W. Wu, L. J. Lu, and X. Y. Xiong, "Generalized ant colony optimization for economic dispatch of power systems," in *Proceedings of IEEE International Conference on Power System Technology*, vol. 1, pp. 225–229, 2002.

[17] J. G. Vlachogiannis, N. D. Hatziargyriou, and K. Y. Lee, "Ant colony system-based algorithm for constrained load flow problem," *IEEE Transactions on Power Systems*, vol. 20, no. 3, pp. 1241–1249, 2005.