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A Hybrid Method for Multi-Area Generation Expansion using Tabu-search and Dynamic Programming

Panida Jirutitijaroen, *Student Member, IEEE*, and Chanan Singh, *Fellow, IEEE*

***Abstract*— This paper combines Tabu search with an optimization technique using dynamic programming for the solution of generation expansion and placement considering reliability in multi-area power systems. Instead of random selection, initial solution for Tabu search is obtained from optimizing a simplified problem utilizing dynamic programming and reliability assessment technique called global decomposition. The comparison between random initial solutions and the proposed method is made. The method is implemented for an actual 12-area power system.**

***Index Terms*— Multi-area Power System, Reliability, Tabu Search, Power System Optimization, Global Decomposition, Generation Adequacy, Dynamic Programming.**

I. Nomenclature

A. Indices

s Source node
t Sink node
i,j Network nodes
I $\{1,2,\dots,n\}$ Set of network nodes

B. Parameters

$\overline{G}_i$ Capacity of existing generation arc i (MW)
a_i^G Cost of an additional unit at node i (\$/MW)
C^G Capacity of an additional generator (MW)
N^G Total number of additional generators
$\overline{L}_i$ Capacity of load arc i (MW)
$\overline{T}_{ij}$ Capacity of existing tie line arc ij (MW)
a_{ij}^T Cost of a tie line between nodes i and j (\$/MW)
C^T Capacity of an additional tie line (MW)
N^T Total number of additional tie lines
R Total available budget (\$)
n Number of areas in the network

C. Decision variables

X_{ij} Flow from node i to j
X_i^G Number of additional generators at node i, integer
X_{ij}^T Number of additional tie lines between nodes i and j where $(i,j) = (j,i)$, integer

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P. Jirutitijaroen and C. Singh are with the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843 USA (e-mail: pjirut@ece.tamu.edu; singh@ece.tamu.edu).

II. Introduction

Multi-area reliability analysis has two major approaches, Monte-Carlo simulation and state-space decomposition. In Monte-Carlo simulation, failure and repair history of components are created using their probability distributions and reliability indices are estimated by statistical inferences. The idea of state-space decomposition [8] [10] [11] [12] [13], is to efficiently classify the system state space into three sets; acceptable sets (A sets), unacceptable sets (L sets), and unclassified sets (U sets) while the reliability indices are calculated concurrently. The concept of Global Decomposition is based on the fact that decomposition depends on state capacities and not state probabilities. With this approach, the additional generators in prospective areas can be included in the system for one time decomposition. This global state space is valid for all generation combinations. The unavailability (forced outage rate) of additional generators is also considered in the formulation. The major advantage of this technique is that decomposition is performed only once. Reliability indices of each combination can be evaluated by allocating zero probability to the omitted states.

Both classical and heuristic optimization techniques have been applied to solve generation expansion problem [1] [2] [3] [4] [5] [6] [7]. In particular, [1] proposes dynamic programming to optimally locate the prospective generators in multi-area power systems while utilizing global decomposition as a reliability evaluation tool. One of the contributions of [1] is to explicitly derive loss of load probability equation in terms of decision variables that is the number of additional generators in the system. However, in this approach the optimization is applied to a subset of state space and may not guarantee global optimality since the reliability index is simplified and approximated.

Tabu search [14] is one of many heuristic techniques applied to generation expansion problem. It has been recognized as an efficient method for combinatorial optimization problems. The algorithm is powerful due to the flexible forms of memory in the search space. The search performance, however, depends on a good starting solution.

This paper combines Tabu search with the solution from [1] to obtain optimal solution. The comparison between using randomly generated starting solutions and solution from [1] is made. In the following, problem formulation is first introduced. Next, concept of global decomposition is described. Tabu search algorithm and parameters are presented. The method is then implemented for an actual 12-area power system. Concluding remarks are given in the last section.

III. Problem Formulation

For multi-area reliability evaluation, power system is modeled as a network flow problem where each node in the network represents an area in the system and each arc represents tie line connection between areas. Source and sink nodes are introduced to represent generation capacity and load as shown in Fig. 1. The capacity of every arc in the network is a random variable because generation, tie line and load capacity are random with discrete probability distributions. For computational efficiency, all arc capacities are rounded off to a fixed increment.

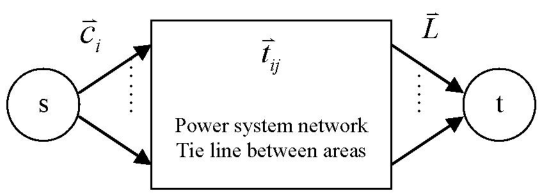

Fig. 1. Power System Network Capacity Flow Model

The decision variables of network flow problem are integer as the number of additional generators is an integer value. The standard formulation is derived in the following with the objective of minimizing loss of load probability subject to cost and network capacity constraints. The additional generators have capacity of C^G MW. The objective function to minimize loss of load probability is given below.

Min

$$f(X)=\Pr\{X_{1t},X_{2t},...,X_{nt}: X_{1t}<\bar{L}_1 \cup X_{2t}<\bar{L}_2 ... \cup X_{nt}<\bar{L}_n\} \quad (1)$$

The problem has the following constraints;

Capacity constraints

– Flow in generation arc

$$X_{si} \le \bar{G}_i + C^G X_i^G \qquad \forall i \in I \quad (2)$$

– Flow in tie line

$$\left|X_{ji}-X_{ij}\right| \le \bar{T}_{ij} + C^T X_{ij}^T \qquad \forall i,j \in I, i \ne j \quad (3)$$

– Flow in load arc

$$X_{it} \le \bar{L}_i \qquad \forall i \in I \quad (4)$$

Conservation of flow at node i in the network

$$X_{si} + \sum_{\substack{j\in I\\ j\ne i}} X_{ji} = \sum_{\substack{j\in I\\ j\ne i}} X_{ij} + X_{it} \qquad \forall i \in I \quad (5)$$

Maximum number of additional generators

$$\sum_{i\in I} X_i^G = N^G \quad (6)$$

Maximum number of additional transmission line

$$\sum_{\substack{i\in I\\ i\ne j}} \sum_{j\in J} X_{ij}^T = N^T \quad (7)$$

Budget constraint

$$\sum_{i\in I} a_i^G X_i^G + \sum_{\substack{i\in I\\ i\ne j}} \sum_{j\in J} a_{ij}^T X_{ij}^T \le R \quad (8)$$

Non negativity

$$X_{ij}, X_i^G, X_{ij}^T \ge 0 \qquad \forall i,j \in I \quad (9)$$

The expression within the parenthesis in equation 1 represents the system loss of load event. The problem is thus formulated to minimize the loss of load probability index subject to cost constraint. If the optimal system reliability obtained through this process does not satisfy the requirements, the cost constraint can be relaxed to allow more additional generators in the system and the LOLP can be re-optimized

All possible additional generation units are included in each prospective area of the system before performing global decomposition. In the global decomposition process, constraints (2) to (7) and (9) have already been included. The problem has only one additional constraint which is the budget constraint (8).

IV. Concept of Global Decomposition

The system state space consists of generation states in each area and inter-area tie line states. It is defined as (10).

$$\Omega = \begin{bmatrix} M_1 & M_2 & \dots & M_N \\ m_1 & m_2 & \dots & m_N \end{bmatrix} \quad (10)$$

where

M_k Maximum state of arc k

m_k Minimum state of arc k

N Number of arcs in the network

A system state, y, can assume any value between its minimum and maximum state as shown in (11).

$$y = [y_1 \quad y_2 \quad \cdots \quad y_N] \quad (11)$$

where $m_k \le y_k \le M_k$

y_k State of arc k

Global decomposition approach analytically partitions the state space into the following three different sets of states.

1. Sets of acceptable states (A sets): The success states that all area loads are satisfied.
2. Sets of unacceptable states (L sets): The failure states or Loss of load states that some area loads are not satisfied.
3. Set of unclassified states (U sets): The states that have not been classified into A or L sets.

The process of partitioning the state space into A and L sets involves determining maximum flow in the network. Ford-Fulkerson algorithm is implemented with breadth-first search for finding existing flow in the system. At the beginning of the decomposition, state space (Ω, as in (10)) is the first U set, unclassified set. At every step of decomposition, one A set, N L sets and N U sets are generated from one U set. The A sets will be deleted to minimize memory usage since the goal of this evaluation is to extract all L sets for system loss of load probability calculation. The U sets have to be kept and partitioned further to A, U and L sets.

The concept of global decomposition is based on the fact that decomposition depends only on state capacities and not the state probabilities. This allows us to include the maximum possible number of generators in each area in the decomposition. The sets obtained from this state space are valid for all scenarios of additional generators. Probability of each scenario can then be evaluated by allowing zero probability for the excluded states because of the omission of corresponding additional generators included in the original decomposition.

V. TABU SEARCH ALGORITHM

Tabu search is an intelligent search procedure that has been widely applied to combinatorial optimization problems. The procedure starts with an initial solution. Neighborhood solutions are then created by some pre-specified neighborhood function. Objective function value of these neighborhood solutions is evaluated. The decision on moving from current solution to the next solution is made based on adaptive memory in Tabu list and current aspiration level. This list is vital since it prevents cycling in the search procedure.

In this application, neighborhood function is simply a random sampling of location to add and drop one generator. Objective function is calculated from global decomposition technique. From computational experiment, it is efficient to sample 8 neighborhood solutions and keep 3 moves in Tabu list. The algorithm is presented in the following.

Initialization, $k = 0$

- Initial feasible solution, $\vec{x}^0 = \begin{bmatrix} x_1^0 & x_2^0 & \ldots & x_n^0 \end{bmatrix}$
- Initialize Tabu list, T^0, and aspiration level, $A^0 = f(x^0)$
- Initialize best solution, $\vec{x}^* \leftarrow \vec{x}^0$

where

x_i^k Number of additional units in area i at iteration k

$\vec{x}^k$ Current solution vector at iteration k

T^k Tabu list

A^k Aspiration level at iteration k which is the reliability Index in this application

$f(\cdot)$ Objective function value of solution vector

While iteration $k <$ maximum iterations do the following,

Step 1. Generate neighborhood solutions, $\{\vec{x}^{nbhd}\} \subset N(\vec{x}^{k-1})$

where

$\{\vec{x}^{nbhd}\}$ Set of neighborhood solutions

$N(\cdot)$ Neighborhood function generation

Step 2. Compute objective function values, $\{f(\vec{x}^{nbhd})\}$ and find the best neighborhood solution, $\vec{x}^{nbhd,best}$

where $\vec{x}^{nbhd,best} = \arg\min\{f(\vec{x}^{nbhd})\}$

Step 3. Check move with T^{k-1}

- If not in T^{k-1}:
  - $\vec{x}^k \leftarrow \vec{x}^{nbhd,best}$, $A^k \leftarrow f(\vec{x}^{nbhd,best})$, and update T^k
  - If $f(\vec{x}^{nbhd,best}) < f(\vec{x}^*)$ then update best solution, $\vec{x}^* \leftarrow \vec{x}^{nbhd,best}$
  - Advance $k \leftarrow k+1$ and go to step 1.
- If in T^{k-1}:
  - Check aspiration criteria, if $f(\vec{x}^{nbhd,best}) < A^{k-1}$, then $\vec{x}^k \leftarrow \vec{x}^{nbhd,best}$, $\vec{x}^* \leftarrow \vec{x}^{nbhd,best}$, $A^k \leftarrow f(\vec{x}^{nbhd,best})$, and update T^k
  - Otherwise, advance $k \leftarrow k+1$ and go to step 1.

Note that in this application, a move is stored as number of the area that a unit is added in the solution vector. A move is checked by comparing the area that a unit is dropped in the solution vector with number of areas in the Tabu list. This criterion prevents cycling since it checks whether the area that a generator is dropped has a generator added in the previous iteration or not. If a generator has been added to this area in previous iteration, we rather not drop it out in current iteration.

VI. A TWELVE-AREA TEST SYSTEM

A 12-area power system is shown in Fig. 2. The test system is a multi-area representation of an actual power system [9] that has 137 generation units and 169 tie line connections between areas. Transfer capabilities between areas are shown in Appendix A. All the tie lines in the system is assumed to have a mean repair time of 8 hours and a failure rate of 10 per year.

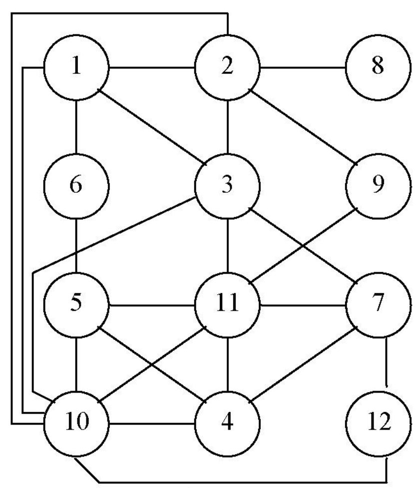

Fig. 2. Twelve Area Test System

TABLE I shows area generation and loads as well as availability and cost per generator in prospective areas which are areas 1 to 5, and 9 to 12. It is assumed that the additional generators have capacity of 200 MW each. The expansion budget is assumed to be \$1 billion. Maximum number of additional units allowed in each area is four units, which gives 495 possible generator combinations. System loss of load probability before unit additions is 0.010169.

TABLE I
GENERATION AND LOAD PARAMETERS OF TWELVE AREA TEST SYSTEM

Area *j*	Load (MW)	Generation (MW)	FOR of additional units	Cost ($m)
1	1900	2550	0.025	250
2	18300	23600	0.025	250
3	10250	15100	0.025	250
4	2200	3100	0.025	250
5	600	900	0.025	250
6	0	550	-	-
7	0	3500	-	-
8	0	400	-	-
9	1200	2100	0.025	250
10	2400	3100	0.025	250
11	2850	4150	0.025	250
12	850	900	0.025	250

TABLE II shows the solution obtained from [1] and solutions from random sampling for comparison in the next section. These solutions are used as starting solutions in Tabu search procedure in the next section.

TABLE II
SOLUTION FROM AN OPTIMIZATION METHOD AND FROM RANDOM SAMPLING

Area	1	2	3	4	5	9	10	11	12
Solution from optimization	0	0	1	3	0	0	0	0	0
Random Sampling 1	1	1	0	0	0	1	1	0	0
Random Sampling 2	0	0	0	1	0	0	1	0	2
Random Sampling 3	0	0	1	1	1	0	0	1	0

VII. COMPARISON RESULTS

Each initial solution in TABLE II is used in Tabu search procedure. The algorithm iterates for 10 times. The comparison between results using initial solution obtained from dynamic programming and those from random sampling are made. Fig. 3. shows objective function values at each iteration resulting from different starting solutions.

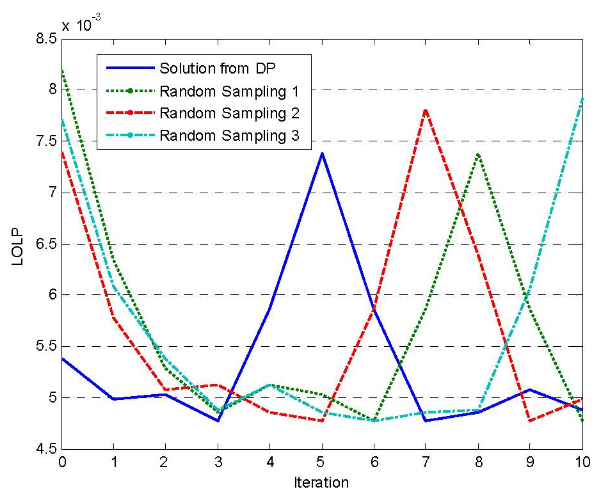

Fig. 3. Comparison of algorithm efficiency produced from different initial solutions

The optimal solution found from enumeration is to locate 2 generators in area 2 and 2 generators in area 4. Random sampling 1, 2, and 3 reach optimal solution at the 6th, 5th, and 6th iteration. Initial solution from optimization reaches optimal solution at the 3rd iteration.

Even though the difference in number of iterations is small, initial solution from optimization provide better assurance of getting good solution than those from random sampling. In actual application, optimal solution is not known; therefore, there will be no guarantee at which iteration it will be reached. Initial solution from optimization at least offers a solution that is close to optimal and likely to achieve it in timely manner.

VIII. CONCLUSION

A combination of heuristic technique and classical optimization is proposed to find an optimal generation location in multi area power systems. The problem has reliability objective function that complicates the optimization process. In [1], dynamic programming is applied to the simplified problem. Global decomposition is used as reliability evaluation tool. The produced solution is near optimal and can be used as a good starting solution for heuristic techniques. Tabu search algorithm is implemented in this paper to search for the optimal solution.

The proposed approach is efficient and ensures a better optimal solution when initial solution from optimization is used. The comparison between randomly selected initial solutions and initial solution from [1] is made. The algorithm reaches optimal solution faster with initial solution from optimization procedure than with random initial solutions. Other meta-heuristic techniques such as Particle Swamp Optimization (PSO) or Simulated Annealing (SA) can also be applied along with classical optimization procedure.

APPENDIX

A. Transfer Capability of a 12-area Power System

Transfer capability of a 12-area power system [9] is shown in TABLE A.I.

TABLE A.I
TRANSFER CAPABILITY

From Area	To Area	Transfer Capability (MW)
1	2	4550
1	3	300
1	6	100
1	10	150
2	3	1050
2	8	150
2	9	900
2	10	450
3	7	400
3	10	200
3	11	50
4	5	50
4	7	300
4	10	200
4	11	150
5	6	400
5	10	50
5	11	650
7	11	350
7	12	950
9	10	150
9	11	150
10	11	150
10	12	100

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