Evolutionary Multi-objective Optimization of Substation Maintenance using Markov Model

C. S. Chang and F. Yang

Abstract—Improving the reliability and reducing the overall cost are two important but often conflicting objectives for substations. Proper scheduling of preventive maintenance provides an effective means to tradeoff between the two objectives. In this paper, Pareto-based multi-objective evolutionary algorithms are proposed to optimize the maintenance activities because of their abilities of robust search towards best-compromise solutions for large-size optimization problems. Markov model is proposed to predict the deterioration process, maintenance operations, and availability of individual components. Minimum cut sets method is employed to identify the critical components by evaluating the overall reliability of interconnected systems. Pareto-fronts are generated for comparisons with other substation configurations. Results for four different substation configurations are presented to demonstrate potentials of the proposed approach for handling more complicated configurations.

Index Terms—Multi-objective evolutionary algorithms, Pareto front, Dynamic Markov model, Minimum cut sets.

I. INTRODUCTION

Preventive maintenance aims to improve reliability of equipment whose failure can be costly. Minimal preventive maintenance was proposed to achieve the aim with limited effort and effects [1]. In contrast, major maintenance restores a component to the “as good as new” condition [2]. Proper maintenance activities provide high availability but with sharp maintenance-cost increase. Thus, it is necessary to best tradeoff between reliability and cost by optimizing both the time and the extent of maintenance. Various mathematical models were reviewed [3] for inspection maintenance, condition-based maintenance, and single/multi-component replacement/repair of industrial systems. As deterioration is stochastic, probabilistic models are usually applied to evaluate maintenance policies. Markov chain model is very useful to establish a quantitative connection between reliability and maintenance and effects of maintenance [4]. A similar probabilistic model was established for transformers [5]. Although single-component models provide detailed information about individual life-cycle deterioration, impacts of topological interdependency of components on the whole is not investigated. Substation reliability is uniquely related to its configuration, and cannot be optimized by considering individual components alone. This paper optimizes the maintenance policy and schedules at the system level covering each substation or beyond. Little work has been done in the systematic improvement of substation reliability through maintenance scheduling of individual components, though some work has been reported on other multi-unit systems, such as generating units [6], infrastructure network [7], bridge[8], and ship structure [9].

Fig. 1 illustrates the proposed approach in three functional blocks with: a device-specific Markov chain model, a system-specific reliability model, and a Multi-objective genetic algorithm. Stochastic and maintenance-dependent dynamic deteriorations of individual component are modeled using a Markov process. Impacts due to changes of substation configuration and maintenance actions on the overall reliability and cost are examined employing the Minimum Cut Sets [10]. This technique evaluates the basic reliability indices at load point. The block of optimization uses the overall cost and Expected Un-served Energy (EUE) as the two objectives for global-optimum search for maintenance frequencies of each substation component.

This paper is organized into eight sections. Section 2 reviews multi-objective optimization algorithms. Section 3 outlines the proposed maintenance model. Sections 4 and 5 describe the technique used for Markov chain model and analysis procedure of Minimum cut sets method. Section 6 presents the Evolutionary algorithm to optimize the multi-objective problem. In section 7, comparative studies of four substation configurations are performed to demonstrate the potential of the proposed approach for applications to large and complex systems. Section 8 concludes the paper.

II. ALGORITHM OF MULTI-OBJECTIVE OPTIMIZATION

Objectives formulated for optimizing maintenance scheduling of power systems are often incommensurable and even antagonistic. Various traditional methods, such as integer programming, branch-and-bound search, dynamic programming, and heuristic techniques, have been reported to solve the problem. However, they can be limited due to high computational efforts that exponentially increase with problem sizes using the methods above. Solution could even be trapped in local optima. Several approaches using Evolutionary Computation were proposed to eliminate the shortcomings...
A hybrid approach of genetic algorithm and simulated annealing using integer representation was applied to optimize the maintenance schedules of generators [12]. Evolutionary programming was also applied to the maintenance scheduling of both generation and transmission [13]. However, all these were formulated in single-objective. For solving multi-objective problems, many proposed approaches on power system optimize only one objective, and treat the other objectives as constraints. Another approach [14] optimizes the long-term maintenance schedules of thermal units by linearly combining all participating objectives into a weighted sum or equivalent single objective, which is optimized using a mix of Genetic Algorithm, Simulated Annealing, and Tabu Search. The weighted-sum method has the advantage of flexibility by simply varying the weights. Unfortunately, the approach requires multiple runs for all combinations of weights, whose choices are often subjective. Advantages of Pareto-based Multi-objective Evolutionary Algorithm over single-objective approach were demonstrated in the maintenance scheduling of aircraft engines [15]. Pareto Fronts are formulated to treat all objectives without priorities, and obtained where none of the objectives can be improved without degrading the others. The approach can also deal with non-continuous objective functions and large scale search space, which are difficult with many traditional methods.

III. LAYOUT OF COMBINED MARKOV AND SUBSTATION RELIABILITY MODELS

As shown in Fig.1, a two-level integrated optimization model is proposed: the device-specific level and system-specific level. By neglecting variations of reliability due to topological inter-dependence of components, the device-specific level evaluates the reliability of each component using a series of Markov chain models. Each model represents one decision interval. The system-specific level deals with the overall effect of individual components within the substation. A fuller description is given as follows:

(1) the whole scheduling horizon is divided into \( T \) intervals, and the maintenance activities to be taken on individual component during decision interval \( t \) are given by the minor and major maintenance frequencies, represented by \( (f_{M}, f_{M}) \),

(2) transition probabilities are constant during each decision interval, but might vary in the next interval according to the performed maintenance actions and conditions of components,

(3) using the minor and major maintenance actions as input, the Markov chain model will produce the availability and maintenance cost of individual component,

(4) system-configuration-related and load-demand-related parameters have to be predefined for the system level, which produce the overall cost and EUE at individual load point, and

(5) objectives to be optimized are the outputs of system-specific model, and the multi-objective optimization method will guide the search towards optimal maintenance policies over the whole scheduling period.

IV. COMPONENT-SPECIFIC MARKOV CHAIN MODEL

A. Homogeneous Markov Model within One Decision Interval

Markov chain relates maintenance policies of each component with its deterioration process, which is described in a finite number of states, i.e., \( S = \{1, 2, \ldots, N\} \) in this paper. Without any maintenance actions, the condition of the component at discrete time \( t = 1, 2, \ldots \), undergoes deterioration in a Markovian manner. On the other hand, should proper maintenance actions be carried out, the component will be restored from the current state back to a better state with given probabilities. Therefore, preventive maintenance is essential to reduce or even eliminate accumulated deterioration. More information about the Markov chain is given in [16]. An \( N \)-state discrete-time Markov process in one decision interval is shown in Fig. 2.

A brief description of the states is given below:
As-good-as-new state \((S_1)\): In this state, no deterioration has occurred to this component.

Deterioration states \((S_2, \ldots, S_N)\): In these states, the component can still operate but with potential failures.

Maintenance activities: \(f_{M,i}\) and \(f_{M,f}\).

Given the transition matrix \(P\) for the Markov chain, a component transits from a state \(i\) to \(j\) with a transition probability \(p_{i,j}\) as time progresses. From the deteriorated state \(i+1\), this component can either continue to deteriorate with a transition probability \(p_{i+1,i+2}\), or go back to a better state with transition probability \(p_{i,j}\), because of the appropriate maintenance actions. For completeness, the model also incorporates random failures, where the system can transit directly from any present state to the failure state with probability \(p_{i,f}\).

### B. Dynamic Decision-varying Markov Models in Different Decision Intervals

The Markov model is homogeneous within each decision interval. However, as the model advances to the next interval, a new set of transition probabilities is used due to the performed maintenance actions. Generally, when maintenance is performed more frequently, the new transition matrix is more likely to make a transition from a deteriorated state to a better one. This dynamic model utilizes two matrices, \(P^t\) and \(P^{t-1}\), to denote the transition matrices in decision intervals \(t-1\) and \(t\). The future transition matrix largely depends on the present one. Therefore, these two transition matrices have been related to each other by assuming that the ratio of two future transition probabilities and the ratio of two present transition probabilities are equal\[17\]. In this paper, the relationship between \(P\) and \(f_{M,i}\) and \(f_{M,f}\) can be estimated exhaustively from collected maintenance date. Therefore, the future transition matrix can be computed by:

\[
P^t(f_{M,i}, f_{M,f}) = \sum_{i=1}^{N} P^t(f_{M,i}, f_{M,f} | S_{i-1} = i) P(S_{i-1} = i)^t (1)
\]

where \(P^t(f_{M,i}, f_{M,f} | S_{i-1} = i)\) is the conditional transition probability matrix, influenced by the maintenance actions taken in interval \(t-1\), given the component is in the state \(i\). \(P(S_{i-1} = i)\) is the probability in state \(i\) at the beginning of interval \(t-1\). We cannot know the exact deterioration state of the component, but it could be inferred from the past history, which involves all of the performed maintenance actions. In this way, the dynamic Markov process evolves and the probabilistic law of transition can be controlled by making maintenance decisions. To represent a decision-varying transition probability matrix, the Markov process is modeled as shown in Fig. 3. Each box contains the Markov model for one decision interval.

In the decision interval \(t\), availability is used to measure the reliability of component. Availability is the sum of the probabilities of all working states. Therefore:

\[
A_a = \sum_{i=1}^{N} P(S_i = i) (1)
\]

For component \(a\), the Maintenance Cost, \(C_{ma,a}\) is calculated using the equations below:

\[
C_{ma,a} = C_{min,a} \sum_{i=1}^{T} f_{M,i} + C_{maj,a} \sum_{i=1}^{T} f_{M,i} (2)
\]

where \(C_{min,a}\) is the cost of minor maintenance, whereas \(C_{maj,a}\) is the cost of major maintenance for component \(a\).

### V. SYSTEM-SPECIFIC RELIABILITY MODEL

Frequent maintenance usually leads to higher reliability but inevitably higher cost. Collective effects on substations with multiple components are somewhat more complicated. Therefore, optimization of maintenance scheduling for substations must be extended from component-specific to system-specific. In such context, a system reliability model is used in addition to the Markov chain model to reflect the impact of multiple-component deteriorations. We employ Minimum cut sets method to access the reliability of system because the failure of load point could occur in different combinations of failure events, known as cut sets.

Minimum cut set is defined as the smallest set of components whose failure can lead to the failure of the load point [18]. The analysis of minimum cut sets here consider only up to double contingencies involving simultaneous failures of two components. Higher contingencies are neglected due to their small probabilities. The availability for a cut set of two components can be calculated following the methods for the parallel outage as:

\[
A_{e} = 1 - (1 - A_1)(1 - A_2) (3)
\]

where \(A_1\) and \(A_2\) represent the availabilities of two components respectively. Since each of these overlapping outages will cause system failure, all the overlapping outages are effectively in series from a reliability point of view. The system indices can therefore be evaluated by applying the methods for series components:

\[
A_{es} = \prod_{i=1}^{n} A_i (4)
\]

where \(A_i\) is the availability of the \(i\)th cut set.

At this point, only forced failure is considered. Following the procedure shown in Fig. 4, all the cut sets leading to the failure of individual load point can be identified.
VI. MULTI-OBJECTIVE MAINTENANCE OPTIMIZATION

A. Formulation of Optimization Objectives

Normally, the configuration with minimum overall cost and maximum reliability is the best one. Therefore, we represent these two objectives mathematically so that they can be optimized.

Economic objective—overall cost. The overall cost, $C$, of a substation consists of two parts—capital cost and maintenance cost, which can be calculated by:

$$ C = \sum_{a=1}^{M} C_a + CapC \times Rate $$

where $M$ is the number of component in this substation. $CapC$ is the capital cost, and $Rate$ is the interest and depression rate.

Reliability objective—EUE. It measures the reliability worth associated with the cost to the customers due to the failure. It is given by:

$$ EUE = \left( \sum_{p=1}^{T} \left( \sum_{j=1}^{m} (1 - A_p) \times L_p, \right) \right) / T $$

where $m$ is the number of load points in one substation, and $A_p$ is the availability at load point $p$, and $L_p$ is the average loss of load (MW) due to failure at load point $p$ in one decision interval. $T$ is the number of decision intervals. EUE is a sum of energy unserved over every decision interval.

Basically, the overall cost will increase as the EUE reduces. Both of them are functions of the maintenance frequencies ($f_{m,o}$, $f_{m,r}$), thus they can be handled as two non-commensurable and contradictory objectives. Therefore, the multi-objective problem can be easily formulated as follows:

$$ \text{Optimize } F(x) = \text{Minimize } (f_1(x), f_2(x)) $$

where $f_1(x)$ denotes the economic objective, overall cost, while $f_2(x)$ denotes the reliability objective, EUE. Variable $x$ is the decision variable containing the potential maintenance frequencies ($f_{m,o}$, $f_{m,r}$).

B. Evolutionary computation techniques

Recently, different Evolutionary algorithms were reported in the literature pertaining to the multi-objective problems. Among them, Multi-objective Genetic Algorithm [19], Non-dominated Sorting Genetic Algorithm [20], and Elitist Non-dominated Sorting Genetic Algorithm [21] received great attention. A Multi-objective genetic algorithm is proposed in this paper for its efficiency and ease to implement. The diagram of the optimization mechanism is shown in Fig. 5.

First, an initial set of candidate solutions is generated randomly. A binary encoding method is used currently for its fast computation and easy manipulation by evolutionary operators. Each maintenance frequency is represented by a 3-bit binary alphabet to guarantee that the value can be varied within the range of 0 to 7 per time interval.

After the initialization, the Evolutionary algorithm evaluates the individuals. The rank of an individual corresponds to the number of chromosomes in current population by which it is dominated [21]. Fitness assignment to a population of $N$ individuals follows the procedure below:

- sort population according to rank,
- assign fitness to individuals by interpolating from the best (rank 1) to the worst (rank $n \leq N$), and
- average fitness of individuals with the same rank, and individuals are penalized according to the population density of the corresponding region of the trade-off surface:

$$ F_i' = \frac{F_i}{\sum_{j} sh(\delta_j) } $$

where $F_i'$ is the shared fitness of individual $i$, and $F_i$ is the original fitness. $\delta_i$ is the value of sharing function, which measures the distance between the objective function, and $\sum_{j} sh(\delta_j)$ is the niche count.

Ranking and selection are the driving force of the Evolutionary algorithm for selecting the most promising chromosomes from the parent pool to generate a new mating pool. High-fitness individuals, with high reliability and low cost, stand a better chance of being selected as parents for the next generation. Several selection schemes, like roulette-wheel, tournament selection, and linear and exponential ranking
selection, can be used [22]. We chose roulette-wheel selection here. After selection, 1-point crossover is used to produce offspring solutions that have the combined features from their parents. Mutation is then applied to avoid local minimal and prevent chromosomes from becoming too similar to each other. The resulting population is evaluated using the ranking scheme and used as a new parent population. Two randomly-based evolutionary operators, known as crossover and mutation, evolve the populations towards optimality.

VII. CASE STUDIES AND DISCUSSIONS

A. Case Description and Assumptions

We made the following assumptions on the four substation configurations of Fig. 6:

1. availabilities of transmission lines feeding the substations are 100%, meaning that they are completely reliable,
2. only transformers (T1 and T2) and circuit breakers (B1~B6) are modeled with the three-deteriorated-state Markov chain model and the system reliability model, and
3. each load point has constant average load demand during individual decision interval, while varying from one interval to another.

The capital cost is calculated based on the typical data about the length of bus, number of breakers, transformers and other system equipment. Rate = 12%, N = 3, and T = 12. The capital costs of main equipment are tabulated in Table 1, and initial model parameters are given in Tables 2 & 3.

B. Results and Discussions

In Fig. 7, with its Pareto front occupying the extreme right-hand position, configuration 1 is inferior to all the other configurations in terms of reliability and overall cost in spite of being the simplest. Without any tie breaker B5 or B6, all components in this configuration will be exposed to failures. With configuration 1 eliminated, the Pareto fronts of configurations 2, 3 and 4 are compared for highlighting the relative impacts of tie breakers B5 & B6. Both configurations 3 and 4 require higher cost than configuration 2 at the lower end of the Pareto fronts (points (2.1) to (2.2)). At the higher end of the Pareto fronts, configuration 4 provides higher reliability than configuration 3 at the same cost as seen from points (4.1) and (4.2).

Within the “middle” range where the costs for configurations 2, 3 and 4 are comparable, configuration 4 should also be preferred to configuration 3 for providing higher reliability with the same cost as seen from points (4.2) and (4.3). Should very low cost be required, configuration 2 should be chosen as seen from points (2.1) and (2.2). As a result, configuration 3 would be least preferred since it does not provide the best reliability for the same cost in the middle range and at both ends of the Pareto fronts.

Table I: Equipment and Cost Lists for Substation Configurations

<table>
<thead>
<tr>
<th>Equipment</th>
<th>Bus 1</th>
<th>Bus 2</th>
<th>Bus 3</th>
<th>Main Breaker 1</th>
<th>Main Breaker 2</th>
<th>Main Breaker 3</th>
<th>Tie Breaker 1</th>
<th>Tie Breaker 2</th>
<th>Tie Breaker 3</th>
<th>Tie Breaker 4</th>
<th>Tie Breaker 5</th>
<th>Tie Breaker 6</th>
<th>Feeder Breaker 1</th>
<th>Feeder Breaker 2</th>
<th>Feeder Breaker 3</th>
<th>Feeder Breaker 4</th>
<th>Feeder Breaker 5</th>
<th>Feeder Breaker 6</th>
<th>Transformer 1</th>
<th>Transformer 2</th>
<th>Cable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (K$)</td>
<td>76.5</td>
<td>33.8</td>
<td>42.0</td>
<td>34.4</td>
<td>31.0</td>
<td>41.3</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Table II: Parameters of Transformer and Breaker for Markov Chain

<table>
<thead>
<tr>
<th>Parameter</th>
<th>T1-T2</th>
<th>B1-B4</th>
<th>B5-B6</th>
</tr>
</thead>
<tbody>
<tr>
<td>p01</td>
<td>5/8</td>
<td>3/5</td>
<td>45/64</td>
</tr>
<tr>
<td>p11</td>
<td>1/4</td>
<td>1/4</td>
<td>5/32</td>
</tr>
<tr>
<td>p12</td>
<td>3/32</td>
<td>1/10</td>
<td>3/32</td>
</tr>
<tr>
<td>p13</td>
<td>1/32</td>
<td>1/20</td>
<td>3/64</td>
</tr>
<tr>
<td>p21</td>
<td>67/75</td>
<td>11/15</td>
<td>13/15</td>
</tr>
<tr>
<td>p31</td>
<td>1/15</td>
<td>3/15</td>
<td>8/75</td>
</tr>
<tr>
<td>p32</td>
<td>1/25</td>
<td>1/15</td>
<td>2/75</td>
</tr>
<tr>
<td>p33</td>
<td>4/5</td>
<td>5/7</td>
<td>21/25</td>
</tr>
<tr>
<td>p3f</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
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</table>

Table III: Cost Related Parameters

<table>
<thead>
<tr>
<th>Minor Maintenance (K$)</th>
<th>0.50</th>
<th>0.50</th>
<th>0.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major Maintenance (K$)</td>
<td>2.00</td>
<td>2.00</td>
<td>1.50</td>
</tr>
</tbody>
</table>

The tradeoff between cost and availability in optimization and the dynamics of the Markov model are revealed in Fig. 8, showing the effects of maintenance using one optimal solution taken from the “knee” region of the Pareto front of configuration 1. Rapid deterioration of availability occurs with no maintenance taken. To tradeoff with cost, the availability of configuration 1 deteriorates within the first 2 decision intervals but recovers progressively towards a reasonable value after 10 further decision intervals.

VIII. CONCLUSIONS

An integrated and modular methodology has been proposed to schedule effective preventive maintenance on individual components in substation by optimizing the two objectives of overall cost and reliability of the substation as a whole. Markov model is proposed to predict the deterioration process, maintenance operations, and availability of individual components. Minimum cut sets is employed to identify the critical components by evaluating the overall reliability of interconnected systems. Pareto fronts formulated using the two objectives provide a holistic view showing the relative advantages of one substation configuration over the others. Results presented on four different configurations demonstrate...
the potentials and ease of application of the proposed approach for handling more complicated configurations.

Fig. 7. Pareto Fronts of four typical substation configurations

Fig. 8. Availability variation as a function of maintenance actions in entire scheduling horizon (configuration 1)

IX. REFERENCES


X. BIOGRAPHIES

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F. Yang obtained her BE in Hydro-electrical Engineering from Huazhong University of Science and Technology, PR China, in 2005. Since then, she has been working as a PhD candidate in electrical engineering in National University of Singapore. Her research mainly focuses on the maintenance optimization of substation in power systems using Evolutionary Algorithm.