Risk Levelized Maintenance Scheduling in Electric Power Systems

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Abstract: - Scheduling of generating units for preventive maintenance plays an important role in the capacity planning of power systems. Optimal scheduling can be obtained in exponential time, consequently, efforts have been directed toward devising approximation algorithms which find near-optimal schedule. Based on the observation that the maintenance scheduling task and the makespan minimization on parallel machines are equivalent problems, in this paper effective approximation algorithms are presented for the levelized reserve as well as the levelized risk scheduling. These heuristic algorithms are compared with local search methods (simulated annealing and genetic algorithms). A case study for the Hungarian Power System shows that the developed algorithms can achieve a substantial levelization in the reliability indices over the planning horizon.

Keywords: maintenance scheduling, reliability of power systems, parallel machine scheduling, local search

1 Introduction

A reliable power system should have enough reserve capacity to overcome service interruptions caused by random equipment failures. The availability of generating units can be improved by careful preventive maintenance. At the same time this maintenance increases the outage capacity in the power system in those periods when the maintenance is carried out. Therefore the maintenance scheduling of generating units is implicitly related to power system reliability [1].

With the appearance of decentralized power systems there are new characteristic in the maintenance scheduling task [2]. A deregulated power system can be divided into three main segments: generation, transmission and distribution. The main task in these three segments remained the same as before, however, there are rules to comply with unbundling requirements which are established to guarantee the fair competition among the market participants. At the same time each segment has certain responsibilities for the power system reliability. Therefore, they are responsible for performing the necessary maintenance on their equipment.

On the liberalized market unit maintenance scheduling is decided by generation companies where the goal is to maximize their profit. Con-
sequently, these companies try to carry out equipment maintenances in those time periods when the market clearing price is lowest. The aim of the Independent System Operator (ISO) is to provide a required reliability level maximizing the reserve capacity in the power system.

In this paper the maintenance scheduling problem is considered from the ISO point of view. In this context it is assumed that generation companies specify their optimal maintenance scheduling plan and hands it over to ISO. The ISO performs its own optimal maintenance scheduling considering the adequate reliability of the power system. If the two maintenance strategies are close enough in terms of reliability, it will be approved; otherwise the units, which violate the constraints, will be rescheduled.

2 Basic Models of Maintenance Scheduling

Assume that, the planning horizon is one year, which can be divided into (e.g. weekly) time intervals. Basically, there are two different objective functions in maintenance scheduling [1]. Let $c_i$ denote the capacity of the generating units. The installed capacity of the power system is $c = \sum_{i=1}^{n} c_i$. If the forced outage rate (FOR) of unit $i$ is $f_i$ based on the two-state Markovian availability model we can define $X_i$ as the unavailability capacity for unit $i$. $X_i$ s $(i = 1, \ldots, n)$ form a sequence of independent random variables where $X_i = c_i$ with probability $f_i$ and $X_i = 0$, with probability $1 - f_i$.

2.1 Levelized Reserve Method

Let $p_j$ be the peak load in the $j$th time increment. The gross reserve in this particular period is $s_j = c - p_j$, $j = 1, 2, \ldots, m$, where $m$ is the number of time intervals in a year.

Let $n_j$ units be scheduled on maintenance in the time interval $j$, consequently $n - n_j$ are available. The net reserve in this particular interval is $r_j = s_j - \sum_{k=1}^{n} c_{j_k}$ where $j_k$ is the index of the unit in the $k$th position in sequence scheduled in the $j$th time increment.

The reliability level of the power system is proportional to the system reserve, so we have to maximize the minimum net reserve over the time intervals of the scheduling horizon. The objective function of the levelized reserve method is as follows:

$$r_{opt} = \max \left( \min_{1 \leq j \leq m} r_j \right). \quad (1)$$

2.2 Levelized Risk Method

Let $P_j$ denote the system load in the $j$th time period. In the power system the electric loads vary in a given time interval so it can be regarded as random variable.

Let $n_j$ units be scheduled for maintenance in the time interval $j$, consequently $n - n_j$ units are available for generation. Then the LOLP (Loss of Load Probability) index for this particular interval is:

$$LOLP_j = \Pr \left\{ \sum_{k=1}^{n-n_j} X_{j_k} + P_j \leq \sum_{k=1}^{n} c_{j_k} \right\}$$

$j = 1, 2, \ldots, m$,

where $j_k$ is the index of the unit in the $k$th position in sequence scheduled in the $j$th time interval.

An appropriate scheduling ensures a sufficient reliability level over the whole year. Consequently, in the case of risk levelized scheduling, we have to minimize the largest $LOLP$ index over the time intervals of the scheduling horizon:

$$LOLP_{opt} = \min_{1 \leq j \leq m} \max \left( LOLP_j \right). \quad (2)$$

Another commonly used reliability index is the Loss of Load Expectation ($LOLE$):

$$LOLE_j = T \cdot LOLP_j, \quad j = 1, 2, \ldots, m,$$
where $T$ is the length of time period in hours (e.g. 168 hours in weekly periods). The LOLE is the expected time during which the power deficit greater than the available capacity of the power system.

Reliability indices can be determined from the probability distributions of the outage capacities and the system loads in each time interval. In order to calculate the outage capacity, its joint distribution has to be computed from the individual unit unavailability distributions determined by $\text{FOR}$ of the generating units [1].

3 Modeling Approaches
In the literature several criteria and techniques have been employed to develop maintenance plans. Levelized reserve methods seek to equalize the reserve for each time interval of a year (1). In [3] an implicit enumeration algorithm is applied, a commonly used method for solving mixed-integer programs. This is one of the most frequently cited papers in the literature of maintenance scheduling and the first attempt to formulate the problem as an exact discrete optimization task.

Recently, many kinds of computational intelligence methods have been applied to solve the unit maintenance scheduling problem. In [4] the simulated annealing method was used with the result that the algorithm succeeded in finding a solution to large problems. Following this success, in [5] the authors developed a technique to include a genetic algorithm and then incorporate tabu search elements into their method.

In order to solve the maintenance scheduling task [6] suggests an appropriate chromosome representation in the genetic algorithm to accommodate constraints of the schedule and an adequate evaluation function is offered to satisfy optimum criteria. Due to the large search space it is difficult to reach an optimal solution using traditional genetic algorithm. This solution is improved in [7] where the task is divided into several layers.

The power system planning in restructured environment can be formulated for self-interested entities [2]. In the coordination of different goals an optimal trade-off should be achieved between the profit maximization for generation companies and power system reliability. In [8] the maintenance scheduling of generating units in a deregulated power system is formulated in different aspects. It uses genetic algorithm to find the optimum schedule for the preventive maintenance concerning the forecasted market clearing price. [9] suggests schedules using the criterion of maximum profit for the generation company. The objective function includes a penalty component for violation of reliable supply.

The risk-leveling techniques seek to spread the risk evenly as measured by some kind of reliability index (2). This task is much more complex from the computational point of view since in each step of the scheduling algorithm we should calculate the reliability index, which also needs considerable running time, furthermore the objective function will not be linear. In [10] the author took the first step by developing an approximation algorithm based on the notion of the load carrying capacity of generating units. Utilizing the analogy between the maintenance scheduling and the makespan minimization on parallel machines an effective heuristic algorithm was described in [11], which can be applied for both leveling strategies. An application of the method is presented for the Hungarian Power System in [12].

4 Parallel machine problem
Based on the observation that the maintenance scheduling of generating units in power systems and the makespan minimization on parallel machines in production scheduling are equivalent problems, in this paper effective approximation algorithms are presented where heuristic as well as local search algorithms will be applied. An overview on mathematical scheduling is presented in [13]. A state-of-the-art review of the parallel machine problem can be found in [14].

The task is to schedule $n$ independent jobs with $p_1, p_2, \ldots, p_n$ processing times on $m$ identical machines. Each job can be processed by exactly one machine; no machine can work on more than one job simultaneously. There are no
precedence constraints and preemption is not allowed. A schedule is an assignment of the job to a machine. A job sequence determines the completion times of the jobs \( c_1, c_2, \ldots, c_n \). The makespan, defined as \( c_{\text{max}} = \{c_1, c_2, \ldots, c_n\} \), is equal to the completion time of the last job. For any schedule, the load of machines is the total processing requirement of the jobs assigned to this machine. The load of the \( j \)th machine is equal to

\[
V_j = \sum_{k=1}^{n_j} p_{j_k}
\]

where \( n_j \) is the number of jobs executed on the \( j \)th machine, \( j_k \) is the index of job in the \( k \)th position on the \( j \)th machine. Since, the makespan is the load on the most heavily loaded machine, the objective function of the makespan minimization is

\[
\min \left( \max \left( V_j \right) \right)
\]

for all schedules.

4.1 Heuristic algorithms

An effective heuristic for the makespan optimization on parallel machines is the MultiFit algorithm. The makespan minimization is in a sense the dual problem to the well-known bin-packing task. The tasks are in bin-packing thought of as items with weights, which are placed in bins of a given capacity. Our goal is to minimize the number of bins used in the packing. The First-Fit-Decreasing (FFD) algorithm is an attempt to find a near-optimal packing very effectively. In the first step of the FFD heuristic weights are put in decreasing order. Then a packing is built up by treating each item in succession, and adding it to the lowest indexed bin into which it will fit without violating the capacity constraint.

The makespan minimization in the parallel machine scheduling we interest in a different question namely, given the number of bins, how large does the bin capacity have to be. To determine the bin capacity a binary search is executed between the estimated upper and lower bounds of the bin capacity.

Another approach to the makespan minimization came from the two dimensional orthogonal packing. Let a set of rectangular figures be into a given "open-ended" rectangular area. Each rectangular piece is defined by an ordered pair corresponding to the horizontal and vertical dimensions of rectangle. We are concerned with the packing of the pieces in the list into the "big" rectangle so as to minimize the height of the packing; i.e. the maximum height, measured from the bottom edge of the "big" rectangle, of the space occupied by any piece in the packing. Obviously, there can be wasted spaces ("holes") in the “big” rectangle. In the makespan minimization task we need a relaxation of this problem where those parts of the last placed rectangle, which do not contact the upper edge of packed rectangles, are allowed to fall down. That means we push them down while they touch the top of replaced rectangle or the bottom edge of the "big" rectangle. It is clear that if the horizontal dimensions in the relaxed task are the same, the rectangular packing is equivalent to the makespan minimization for the parallel machines. In the first step we construct a priority list in decreasing order corresponding to height or width of the rectangles.

For the solution of packing, a good heuristic is the so-called Bottom-up Left-justified (BL) algorithm. The BL algorithm packs the pieces one at a time as they are drawn in sequence from the list. When piece is packed into "big" rectangle it is first placed into the lowest possible location, and it is left justified at this vertical position. A generalization of the BL algorithm: in each steps we determine which rectangles cause the most serious problem that is which piece will increase most seriously the height in the actual packing. This rectangle is placed according to the BL strategy. Observe that this algorithm does not need a fixed priority list. In this paper this scheduling strategy is named as MinMax algorithm.
4.2 Local Search Methods

Variations of local search algorithms have been proposed based on analogues with processes in nature such as statistical physics (simulated annealing), biological evolution (genetic algorithms), and neurophysiology (artificial neural networks) [15].

A commonly used technique in optimization is the threshold algorithm, which starts from a feasible solution, then selects a solution from the neighbourhood of the current value. Under the procedure it compares the difference in objective function. If the difference is below a given threshold, the neighbour replaces the current solution. Otherwise, the search continues with the last solution. In the course of the algorithm's execution, the threshold values are deterministic and gradually lowered. Simulated annealing uses randomized thresholds where solutions corresponding to large increases in objective function have a small probability of being accepted, whereas solutions corresponding to small increases have a larger probability of being accepted.

Genetic algorithm starts with a large commune of chromosomes (e.g. binary strings) known as the initial population. The initial values of chromosomes correspond to discrete values of a matrix (population matrix). The initial population is passed to the cost function (fitness) evaluation. From this initial population a large portion of the high cost chromosomes are discarded through natural selection (survival of the fittest). First, the costs associated chromosomes are ranked from lowest cost to highest cost. Then, only the best members of the population are kept for each iteration while the others are discarded. Two chromosomes are selected from the mate in pool to produce two new offspring. Pairing takes place in the mating population until offspring are born to replace the discarded chromosomes. Random mutations are performed with some small probability to make variety into the population and to avoid fast convergence to a local optimum. The next step ranks the new population and selects a new mating pool. The process continues until some stopping criteria are satisfied.

5 Maintenance Scheduling Algorithms

In the previous section several approximation algorithm were described, which are developed essentially for the makespan minimization of parallel identical machines and other resource scheduling tasks.

5.1 Equivalency with Parallel Machine Problem

If the duration of maintenance is one time period for any generating units; any generating units can be scheduled in any time periods and we assume that the peak loads are constant during the year the maintenance scheduling problem is equivalent to the makespan minimization on identical parallel machines [11]. Note that the time intervals in the maintenance scheduling task correspond to the machines in the parallel machine scheduling. The capacities of the generating units correspond to the processing times of the jobs on the parallel machines so the planned outages in the several time periods correspond to the load on the machines. Consequently, the objective function of the levelized reserve scheduling (1) is the same as the objective function (3) for the parallel machine problem where the makespan is minimized. In the levelized risk method using LOLP reliability index we should minimize the probability that the outage capacity of the power system greater than a fixed value (the available capacity of the power system). In the parallel machine problem this objective function is equivalent to minimizing the probability when the makespan is greater than a fixed value.

5.2 Approximation Algorithms

Basically, the task is to place two-dimensional rectangles with given width (maintenance requirements in weeks) and given length (capacity of the units in MW) considering the weekly peak loads and satisfying the constraints of the maintenance (e.g. fixed maintenance periods, not allowed time intervals for unit maintenance,
number of units that allowed to be simultaneously on outage).

The first step is to make a priority list in decreasing order corresponding to the length of maintenance requirements and the capacities of generating units. The next step is to select a packing strategy. In this paper we applied Bottom-up Left-justified (denoted by BL), MinMax (MM) and MultiFit (MF) heuristics. In some cases we modified the obtained result in such a way that we alter the scheduling of one or few units (these versions are distinguished denoted by "r"). This rescheduling of the units can be carried out in random or deterministic way.

In the genetic algorithm (denoted by GA) the pool is generated calculating a certain permutation of feasible solutions. The genetic operators operate these index sequences from which we construct schedules using any heuristic algorithms. In the simulated annealing approach (denoted by SA) we started a random solution, which is a feasible scheduling of the generating units. This solution is altered according to the scheme of local search strategy.

6 Results
A demonstrative example from the Hungarian Power System is presented to show the application of the approximation algorithms described in Section 5. The system consists of 41 thermal and 4 nuclear units located in 17 different power plants. The total capacity of the considered power system is 7070 MW. The yearly peak load is 5800 MW. The year was divided into 53 weekly time increments.

In the first test calculation scheduling constraints are not considered i.e. any generating units can be scheduled in any time periods. Two local search (GA and SA) and three heuristic methods (BL, MM, MF) were applied in reserve leveling option where in case of BL and MF heuristics we calculated the objective function without and with rescheduling.

In Table 1. the results are summarized where the peak load, the gross reserve and the net reserve are shown characterized by their minimum, maximum, average values and their standard deviation over the scheduling horizon. The best net reserve can be obtained using MultiFit heuristic with replacing (MFr) where the optimal net reserve is 1270 MW with standard deviation of 45 MW. The MM and the BL algorithms can achieve much more unevenly net reserve (standard deviations are 105 MW and 104 MW, respectively) and lower optimal system reserve (1220 MW).

In the second version of the test calculation from the 45 generating units 24 units are not allowed to maintain in winter seasons (January, February, November, and December) and there is no maintenance in the New Year eve and Christmas period. Obviously, under these constraints more disadvantageous net reserve pattern can be obtained as we performed in the previous calculation. The best algorithm as in the first version is the MFr (the optimum value of the net reserve is 1250 MW with the standard deviation of 160 MW). The MinMax heuristic can achieve 1200 MW system reserve; the standard deviation is 164 MW. Moreover in this version the LOLE indices were calculated. Using the MFr heuristic the highest LOLE index is 0.0579 hour while the MM can achieve 0.0781 hour (see Table 2).

In Fig. 1. the net reserves and LOLE indices are shown over the scheduling horizon applying the MFr and MM algorithms. The MM heuristic in levelized risk option exhibits more unevenly distributed net reserves in comparison with the MFr strategy but it can achieve more uniformly distributed risk values. Using the MFr in the leveling reserve option the highest (worst) LOLE index is 0.0579 hour (standard deviation is 0.0122 hour) while the MM algorithm in levelized risk option performed 0.0509 hour (standard deviation is 0.0105 hour).

7 Conclusion
Based on the observation that the maintenance scheduling of generating units in power systems and the makespan minimization on parallel machines in scheduling theory are equivalent problems, in this paper effective approximation algorithms are presented. Using a demonstrative example from the Hungarian Power System, these heuristics are compared with each other and
with the local search methods in the levelized reserve scheduling strategy. The heuristic (constructive) methods are much more effective from the computational point of view even they achieved better system reserve in comparison with local search techniques.

Using the MM heuristic in the levelized risk option nevertheless the net reserve showed more irregular fluctuation, the algorithm can achieve more uniformly distributed reliability indices over the year which results in a more reliable power system. The application of the method yielded higher reliability level at critical time intervals of the year (see Fig. 1).

 References:


Table 1
Results of the Levelized Reserve Scheduling

<table>
<thead>
<tr>
<th>PeakL GrossRes</th>
<th>Net Reserve (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(MW) MM GA SA BL BLr MF MFr</td>
<td>MM GA SA BL BLr MF MFr</td>
</tr>
<tr>
<td>Min</td>
<td>4730 1270 1220 1250 1250 1220 1260 1260 1270</td>
</tr>
<tr>
<td>Max</td>
<td>5800 2340 1640 1730 1610 1670 1580 1560 1500</td>
</tr>
<tr>
<td>Average</td>
<td>5253 1817 1315 1315 1315 1315 1315 1315 1315</td>
</tr>
<tr>
<td>StDev</td>
<td>359 359 105 93 81 104 65 53 45</td>
</tr>
</tbody>
</table>

Table 2
Results of the Levelized Reserve and Levelized Risk Scheduling

<table>
<thead>
<tr>
<th>PeakL GrossRes</th>
<th>Net Reserve</th>
</tr>
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<tbody>
<tr>
<td>(MW) MM GA SA BL BLr MF MFr</td>
<td>ReserveL</td>
</tr>
<tr>
<td>(MW) MM GA SA BL BLr MF MFr</td>
<td>ReserveL</td>
</tr>
<tr>
<td>MM</td>
<td>4730 1270 1200 1220 1220 1260 1260 1250 1150</td>
</tr>
<tr>
<td>Max</td>
<td>5800 2340 2110 2110 2110 1670 1580 1560 2110 2110</td>
</tr>
<tr>
<td>Avg</td>
<td>5253 1817 1315 1315 1315 1315 1315 1315 1315</td>
</tr>
<tr>
<td>StDev</td>
<td>359 359 164 165 180 104 65 53 160 168</td>
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<table>
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<th>Loss of Load Expectation</th>
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<tbody>
<tr>
<td>ReserveL</td>
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<tr>
<td>(hours) MM GA SA BL BLr MF MFr</td>
</tr>
<tr>
<td>Min</td>
</tr>
<tr>
<td>Max</td>
</tr>
<tr>
<td>Avg</td>
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<td>StDev</td>
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Fig. 1: Net Reserves and LOLE indices over the weeks of the year