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A Survey of Generator Maintenance Scheduling Techniques

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Abstract - Many maintenance-scheduling methods have been proposed using conventional mathematical programming methods or heuristic techniques. Heuristic approaches provide the most primitive solution based on trial-and-error approaches. Mathematical optimization based techniques are completely distinct from classical programming and trial-and-error heuristic methods. These techniques have been proposed to solve small maintenance scheduling problems. In this paper we explain the difference between both methods in solving generator maintenance scheduling (GMS) problem.

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A SURVEY OF GENERATOR MAINTENANCE SCHEDULING TECHNIQUES

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A Survey of Generator Maintenance Scheduling Techniques

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I. Introduction

Heurestic techniques may not generally lead to the global optimal for a complex problem, i.e. the procedure tends to fall into a local minimum if a starting point is not carefully chosen. Heuristic methods were used earlier in solving maintenance scheduling problems for centralized power systems because of their simplicity and flexibility. Mathematical optimization based techniques such as integer programming [24], dynamic programming [61-60] and branch-and-bound [43] have been proposed to solve maintenance scheduling problems. For small problems these methods give an exact optimal solution. However, as the size of the problem increases, the size of the solution space increases greatly and hence the running time of these algorithms. These approaches tend to suffer from an excessive computational time with the increase of variables. To overcome this difficulty, modern techniques such as simulated annealing [13-37], stochastic evolution [52], genetic algorithms [32] and Tabu search [51] have been proposed as alternatives where the problem size precludes traditional techniques. These techniques are completely distinct from classical programming and trial-and-error heuristic methods. The GA methods mimics the principles of natural genetics and natural selection to constitute search and optimization procedures. Simulated annealing mimics the cooling phenomenon of molten metals to constitute a search procedure.

The GA and SA approaches have been reported to solve a range of optimization problems in electrical power systems with encouraging results (Mirinda et al.. [43]). The following sections review the some of common math-base and modern heuristic based techniques. The paper is organized as follows: In Section II we presented mathematical techniques, in section III an artificial intelligence approach is described and the conclusion in section IV.

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II. Mathematical Techniques

The Mathematical approaches are mainly based on linear, Integer, and Mixed-Integer Programming (LP, IP, and MIP), Decomposition, Branch-And-Bound (BaB) and Dynamic Programming (DP). In the following sections we describe several mathematical solution techniques, which were used in the literature for solving maintenance scheduling problems.

In the following figure the mathematical techniques are presented.

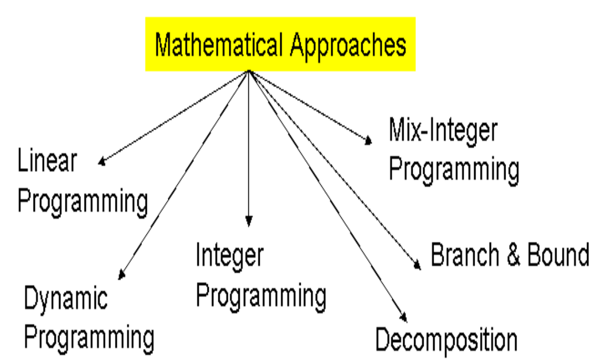

Figure 1 : Mathematical Approaches

a) Linear, Integer, and Mixed-Integer Programming

The most basic mathematical programming technique is linear program (LP). It has been applied with impressive success to problems ranging from familiar cases in industry, economics and transportation to the more extreme cases in behavioral sciences [45]. The LP model refers to an optimization problem in which the objective function and the constraint function are linear variables. Integer programming (IP) is essentially LP with the additional requirement that the variables have to be an integer. If only some of the variables are required to be integer and the others are real, then it became mixed integer programming (MIP). Combinatorial scheduling problems can often be formulated as IP or MIP problems [34],[7],[24].

The cutting plane (polyhedral) technique deals with IP by focusing on LP relaxation. The techniques aim at generating additional linear constraints that have to be satisfied for the variables to be integer. These additional inequalities constraint the feasible set more than the original set of linear inequalities without cutting off integer solutions. Solving the LP relaxation of the IP with additional inequalities then yields a different solution, which may be integer. If the solution is integer, the procedure stops, because the solution obtained is an optimal solution for the original IP. If the variables are not integer, more inequalities are generated [50]. In any LP there is a dual problem to the primary one. These two problems are related to each other with interesting applications. The duality in LP has been used in another solution technique, Benders decomposition.

Shahidehpour and Marwali [54] in their book have used MIP and the Benders decomposition technique to coordinate and optimize maintenance scheduling in a deregulated system.

Yao et al.[46] have developed a model based on mixed integer programming and it is helpful in resource limitations in manufacturing. The non linear functions appearing in the MIP model can be transformed into linear functions with the help of decision variables. This can be solved by using any LP/IP software. The result shows that in the PM based model scheduling system, the equipment availability would increase and become profitable to the manufacturer.

b) Dynamic Programming

In 1957, Dynamic Programming (DP) originates from Bellman and is applicable to a lot of optimizing problems, not just those arising in scheduling [28]. It is one of the more widely used techniques for solving combinatorial optimization problems. DP can be applied to problems that are solved in polynomial time as well as problems that can't be solved in polynomial time. It has proven to be applicable to stochastic problems as well [50].

Dynamic programming is basically a complete enumeration scheme that attempts, with a divide-and-conquer approach, to minimize the amount of computation to be done. The approach solves a series of sub problems until it finds the solution of the original problem. It determines the optimal solution for each sub problem and its contribution to the objective function. At each iteration, it determines the optimal solution for a sub problem, which is better than the previously solved sub problems. It finds a solution for the current sub problems by utilizing all the information obtained before in the solutions of all previous sub problems as well [50].

c) Branch and Bound

The Apart from heuristic methods, the Branch-and-Bound (BaB) technique is probably the most widely used technique in scheduling. Like DP it is an enumeration technique and used to optimize large class problems [28]. It is a type of implicit enumeration method or tree search method, which can find an optimal solution by systematically examining subsets of feasible solutions [43-14].

The Branch-and-Bound procedure consists of the repeated application of the following steps. First, that portion of the solution space (i.e. set of decision variables under consideration) in which the optimal solution is known to lie is partitioned into subsets. Second, if all of the elements in a subset violate the constraints of the minimization problem, then that subset is eliminated from further consideration (fathomed). Third, an upper bound on the minimum value of the objective function is computed. Finally, lower bounds are computed on the value of the objective function when the decision variables are constrained to lie in each subset still under consideration. A subset is then fathomed if its lower bound exceeds the upper bound of the minimization problem, since the optimal decision variable cannot lie in that subset. Convergence takes place when only one subset of decision variables remains and the upper and lower bounds are equal for that subset [49].

d) Benders Decomposition

Bender's method, based on LP duality theory, decomposes the scheduling optimization problem into a master problem and several sub-problems. The master problem in this case involves only the integer variables of the problem, and the sub-problems involve only the continuous variables. The solution process of the master problem starts with almost no constraints. Then the sub-problem is used as a test to check if this solution satisfies the remaining constraints. If so, then the solution is optimal, since the objective has been minimized over all constraints. Otherwise, the most unsatisfied constraint (i.e. the deepest cut) will be added to the master problem, and it will be resolved with the added constraint. The main disadvantages of this approach are the long computational time requirement and the suitable problem model [54].

Because of the combinational nature of the GMS problem, MIP and Bender's decomposition methods are used to coordinate and optimize maintenance schedules. Marwali and Shahidehpour [40] use Benders decomposition for solving maintenance scheduling problems for centralized power system structures. They use Benders decomposition to decompose a complex Integrated Maintenance Scheduler (IMS) problem that represents a network constrained generation and transmission maintenance-scheduling problem, into a master problem and operation sub-problems. By using an IMS, several and complex constraints which bound the selection of scheduling times, are included into the solution method. In this problem, at each iteration, the solution of sub-

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problems generate dual multipliers, which are used to form one or more constraints that will be added to the master problem for the next iteration until a feasible solution is found. Benders approach has been used in different publications [54-42] for solving different problems in deregulated systems. Also, Marwali and Shahidehpour, [41] have used Benders decomposition method to solve a short-term transmission maintenance problem.

III. Artificial Intelligence Approach

Various Artificial Intelligence (AI) techniques for solving the maintenance-scheduling problems of a power system can be found in the literature with different presentations. Artificial Intelligence (AI) includes expert systems, Simulated Annealing (SA), fuzzy logic theory, neural network, evolutionary optimization including evolutionary programming, evolutionary strategy and Generic Algorithm (GA), simulated evolution and their hybrids. This section will present some of theses AI techniques.

a) Simulated Annealing (SA)

Kirkpatrick et al.,[37] and Cerny, [13] independently introduced simulated annealing. Satoh and Nara, [53] and Burk et al.,[9] have considered simulated Annealing (SA) algorithms in solving thermal generator maintenance scheduling problems. The problems were formulated using the economic objective and typical problem constraints. The authors found that SA was faster than integer programming (IP) in finding the same solution for their small and medium-sized problems. Also, the SA approach was able to find a solution for the large system where IP could not be realized due to combinatorial explosion. They used a binary string representation to encode a trial solution and penalty approach to take account of the problem constraints [20].

Annealing, physically, refers to the process of heating up a solid to a high temperature followed by slow cooling achieved by decreasing the temperature of the environment in steps Wong and Wong [57] and Annakkage et al. [4]. By making similarity between the annealing method and the optimization problem, an enormous class of combinatorial optimization problems can be solved following the same procedure of conversion from one equilibrium condition to another, reaching minimum energy of the system [49]. The initialization of the SA method involves the selection of an initial temperature (T_0) and an initial solution in the search. The initial solution may be generated at random or by any other means. If the final solution is to be independent of the starting solution, the initial temperature (T_0) must be high enough to permit an almost free switch of neighbouring solutions. Generally the value of (T_0)is chosen in such a way that it is greater than the maximum possible difference between the evaluation values of two solutions [25].

Finally, the criterion for stopping the algorithm can be articulated either in terms of a minimum value of the temperature, or in terms of the 'freezing' of the system at the current solution. 'Freezing' may be recognized by the number of iterations (or 'temperatures') that have passed without a move being acknowledged that has exceeded a given limit, or by the number of accepted moves in a stage falling below a given value. However, the simplest rule of all is to fix the total number of iterations. The number of iterations needs to be carefully tuned with other parameters to make sure that it corresponds to a satisfactorily low temperature to ensure convergence [21].

Then, the temperature is decreased as the algorithm progresses according to a cooling schedule. The cooling schedule may be adapted by using a large number of iterations at a small number of temperatures or vice versa. The number of iterations at each temperature and the rate at which the temperature is reduced are significant factors in controlling the performance of the SA method. The number of iterations increases with successive temperatures since it is important to spend more time searching at lower temperatures to guarantee that the neighborhood of a local optimum has been entirely explored. Then, the move operator specifies the algorithm for generating a new trial solution from the current solution. Randomly, the move operator selects one variable from the integer strings to be changed. The selected variable is then changed to a random value in the allowed range.

b) Genetic Algorithms (GA)

During the last years, there has been a growing interest in problem-solving systems based on the principles of evolution and machine learning [48-55]; where such systems maintain a population of potential solutions. They have some selection process based on fitness of individuals and some "genetic" operators [49]. In the 1970s, Holland [44] introduced the concept of a genetic algorithm (GA). Like other Artificial Intelligence (AI) the basic idea behind GA was to make computers do what humans do. In order to apply a genetic algorithm to solve an optimization problem, candidate solutions must be encoded using an appropriate representation, such as a numeric string, and an evaluation function must be formulated to assign a quality value to every solution produced.

The GA represents an iterative process, where each iteration is called a generation. Population size specifies how many individuals there are in each generation. With a large population size, the genetic algorithm searches the solution space more thoroughly, thereby reducing the possibility that the algorithm will return a local minimum that is not a global minimum. However, a large population size also causes the algorithm to run more slowly. Each population contains a number of chromosomes, and a chromosome consists of several "genes", and each gene is represented by 0 or 1.

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There are two basic mechanisms that link a GA to the problem it is solving: encoding and evaluation. The encoding is carried out using binary strings (chromosomes) of ones and zeros in each bit, which is the most popular representation. An evaluation function is used to measure the chromosome's performance, or fitness, on the problem to be solved. The GA uses a measure of fitness of individual chromosomes to carry out reproduction. Genetic algorithms apply three genetic operators: selection, crossover and mutation.

i. *Selection Genetic Operator*

There are different types of selection methods [5] such as the following:

- Tournament selection: where a small subset of individuals is chosen at random, then choosing the best individual from that set to be a parent.
- The roulette wheel selection: The most common chromosome selection technique is the roulette wheel selection [32-22]. Roulette selection chooses parents by simulating a roulette wheel, in which the area of the section of the wheel corresponding to an individual is proportional to the individual's expectation. For example, for a given population each chromosome is given a slice of a circular roulette wheel equal to the chromosome fitness ratio. To select a chromosome for mating, a random number is generated, and the chromosome whose segment spans the random number is selected. It is like rotating a roulette wheel where each chromosome has a section on the wheel proportional to its fitness. The roulette wheel is spun, and when the arrow comes to stop on one of the slices, the corresponding chromosome is chosen.

ii. *Cross over*

Crossover specifies how the genetic algorithm combines two individuals, or parents, to form a crossover child for the next generation. The crossover operator is applied with a certain crossover probability, once a pair of parent chromosomes is selected. Generally, a value of 0.7 for the crossover probability produces good results [46]. First, the crossover operator randomly chooses a crossover point where two parent chromosomes "break", and then exchanges the chromosome parts after that point. As a result, two new off-spring are created. There are different types of crossovers for example [5]:

- Single point crossover: where a single locus chosen at random then a parent chromosome break and all bits after that point be swapped.
- Two point crossover: this involves choosing two points at random and swapping the corresponding parts from the two parents defined by the two points.

iii. *Mutation*

Mutation specifies how the genetic algorithm makes small random changes in the individuals in the population to create mutation children. Mutation can occur at any gene in the chromosome with some probability. Typically, the mutation probability is in the range between 0.001 and 0.01.

Mutation provides genetic diversity and enables the genetic algorithm to search a broader space [47]. Genetic algorithms guarantee the continuous improvement of the average fitness of the population, and after a certain number of generations the population evolves to an optimal or near-optimal solution.

Given a clearly defined problem and a binary string representation for candidate solutions, a basic GA can be represented in the following steps [22-44]:

Step 1: Represent the problem variable domain as a chromosome of and define the population size, the crossover and the mutation probability, and the evaluation function.

Step 2: Randomly produce an initial population of chromosomes.

Step 3: Compute the fitness of each one.

Step 4: Choose a couple of chromosomes for mating.

Step 5: Generate a pair of offspring chromosomes by applying genetic operators.

Step 6: Position the formed offspring chromosomes in the new population, then repeat Step 4, until the size of the new population becomes equivalent to the size of the initial population.

Step 7: Substitute the initial (parent) chromosome population with the new (offspring) population.

Step 8: Go to Step 3, and repeat the process until the termination criterion is fulfilled.

Genetic algorithms become popular as a powerful optimization tool appropriate for a diversity of problems. Both GA by it self or a combination of GA and other techniques are broadly addressed in the literature for solving maintenance scheduling for power systems. Negnevitsky and Kelareva [47] have used GA is solving maintenance scheduling in power systems. The objective was to maximize reserve margins subject to maintenance and system constraints. They have designed a representation which is suitable for a variety of problems and appropriate chromosome evaluation is suggested. A case study was solved using GA, and the result shows that chromosome representation plays an important role in GA where it may reduce problem complexity by including constraints. Abdulwhab et al.[1] use the genetic algorithm optimization technique to maximize the overall system reliability for a specified future time period in which a number of generating units are to be removed from service for preventive maintenance.

Baskar et al.[6] has used GA with modified genetic operators, such as string reversal and reciprocal exchange mutation, to solve the generator maintenance scheduling (GMS) problem. They have used three types of encoding; integer encoding, binary for integer

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encoding, and real encoding. The GMS problem is solved to minimize the expected energy production cost and maximizing the reserve objectives subject to maintenance windows, consecutive periods of maintenance, crew, demand reserve and reliability. The result shows that only integer coding GA finds the global optimum solution, irrespective of the nature of the objective function and system size. Also, modified genetic operators were shown to be effective in reducing computation time and improving search efficiency of the GA.

It has been reported that the performance of the GA approach can be improved by combining it with other techniques [51]. The GA/SA hybrid approach has been employed to solve a maintenance scheduling problem by Kim et al., [36]. The hybrid approach presented by Mohanta et al. [45] use the integer encoding for solving the captive power plant maintenance scheduling problem with levelized reserve reliability objective function. From the comparison of results obtained from application of only GA and from hybrid GA/SA techniques for scheduling, can be seen that the hybrid GA/SA solution technique yields better results.

Dahal et al.[20] investigated the applications of GA and SA using an integer representation to encode candidate solutions to GMS test problems with a reliability criterion. The evaluation function is a weighted sum of the objective function and the penalty function for violations of the constraint. The authors concluded that the SA and GA are robust and stable techniques for solving GMS problems.

Dahal et al. [17] propose solving centralized maintenance problems using GA with integer's representation using fuzzy evaluation functions. Since fuzzy logic can be used to deal with multiple objectives, it was used to combine the objective of maximizing reliability and considering the flexibility in the manpower constraint. The fuzzy evaluation function is developed as a combination of a crisp penalty function for inflexible load constraint and a fuzzy penalty function for the objective and the flexible manpower constraints. The results obtained using the fuzzy logic evaluation function were compared with those obtained from GAs with crisp evaluation functions, and the fuzzy logic method was shown to achieve an effective trade-off between reliability and manpower within the allowed flexibility.

Burk and Smith [12] presented a technique named Memetic approach for solving real scale maintenance scheduling problems in centralized structures. The objective was to minimize the sum of the overall fuel and maintenance costs. Memetic is a genetic algorithm combined with Tabu search. Tabu search is a powerful optimization procedure that has been successfully applied to a number of combinatorial optimization problems. Memetic takes the concept of evolution as employed in GA. It has a memory as unit of information instead of gene in GA [23]. A population of information can be created and a good one has a better chance of survival than a bad one, and they can be combined to form new ideas. They investigated the use of Memetic algorithms for solving thermal generator maintenance scheduling problems. A comparison between Tabu search and Memetic algorithm shows that Tabu is more affective for small problems and Memetic algorithm will outperform Tabu search for large problems. Also, they show that the Memetic algorithm using Tabu search as the local optimizer yields greater benefits than simulated annealing which was used previously in solving thermal generator maintenance scheduling problems [53].

c) Multi-stage Approach

A new solution approach was developed by Burk and Smith [11] for solving large size thermal generator maintenance scheduling problems for centralized structures. It is named multi-stage approach. The problem which has been solved by the authors has been tackled by different researchers using different solution techniques such as SA, GA, Memetic and Tabu. Among these algorithms the Memetic algorithm alone can produce quality solutions at the expense of extended run-time. The authors addressed the problem of extended run-times by using a multi-stage approach. Instead of solving the problem in one step, the multi-stage approach segregates the main problem into a series of sub-problems, each can be solved consecutively then the results recombined to form the solution of the original problem. It is not suitable for indivisible problems. It is similar to the rolling-horizon technique, which has been applied to problems such as multipurpose plant scheduling ,commercial fishing fleet scheduling and production scheduling.

The first task of the multi-stage algorithm is to order the units according to some measure of difficulty. An example of the difficulty measure is ordering the units with the least number of possible maintenance starting periods first. Another example is scheduling the units with the highest operating capacity first. In doing so the chance of creating difficulties later on in the process is decreased. Then, the algorithm will fit the easier units in the available gaps. The multi-staging approach picks the first N units and schedules them using the Tabu search or Mimetic algorithm. All other units are left unscheduled. The next N units (most difficult units to schedule) are then placed in the schedule, and so on, until all units have been scheduled. Therefore, each evaluation function can re-use data acquired from the previous evaluation very effectively.

This approach differs from other rolling horizon approaches in that the problem is divided into sub-problems which contain a reduced number of units to be scheduled, rather than sub-problems with a look-ahead set of a further M units from the list to the units currently being scheduled. However at the end of the scheduling, only the first N units are fixed into the schedule. This enables the algorithm to schedule the current set of N units based not only on the units already scheduled (if any), but also to utilize additional information based from looking ahead at the next M units [11].

IV. Conclusion

There are many solution methods, in this paper we reviewed a wide range of mathematical and artificial intelligence approaches. In the literature, these techniques were used to solve different maintenance scheduling problems.

Heuristic methods were used previously in solving maintenance scheduling problems because of their elasticity, but they may not lead to optimal solution for a complex problem. Mathematical techniques such as MIP and Bender's Decomposition, have been proposed to solve generator maintenance scheduling problems for small problems. However, for NP-complete scheduling problems traditional deterministic techniques can fail due to time limits.

Genetic Algorithm (GA) becomes a powerful optimization tool appropriate for a diversity of problems. Gas are based on natural genetic and evolution mechanisms which can be used to solve complicated optimization problems. The key success of GA lies in defining a fitness function that incorporates all constraints. Genetic Algorithm (GA) was found to be a powerful optimization tool for solving different maintenance scheduling for power systems.

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