AN INTEGRATED FRAMEWORK FOR DEVISING OPTIMUM GENERATION SCHEDULES

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Abstract

An integrated framework for generating optimum unit commitment and dispatch schedules is presented in this paper. The work reported here employs a hybrid technique by which a genetic population can be confined to a set of feasible solutions. Heuristics are used to ensure that all the constraints, both linear and nonlinear, are fulfilled for each member of the population. The use of this technique, which combines the advantages of knowledge-based methods with the strengths of evolutionary algorithms, results in considerable reduction in computing time, making its application viable in daily operation scheduling.

Introduction

The main objective of current-day generation planning is to ensure the availability of adequate generating margins, in excess of estimated load levels over the entire planning horizon, in the most cost-effective manner while preserving the system operational constraints.

The problem of generation scheduling belongs to the class of nonlinear constrained optimization problems with minimization of cost as the primary objective of optimization. The planning horizon is usually divided into three categories according to the time periods involved, which can be short-term, medium term or long-term. This paper deals with short-term generation scheduling problem, which primarily deals with unit commitment and their dispatch over a time period of one day to one week.

Short-term generation scheduling is an important activity in system daily operation due to its direct influence upon the quality and economy of the power supplied to the customers. The basic approach to the unit commitment problem is a heuristic method which assumes a preassigned priority or merit order among the units, and generates good, workable solutions with realistic computational requirements [1]. The most popular approach, dynamic programming, involves selecting among the combination of units which satisfy the load demand and have minimum operating costs [2]. This approach, however, suffers from excessive computing time and memory requirements as the problem size increases. Lagrangian relaxation methods [3] have recently been applied for this problem and found superior to the above methods due to their ability to provide solutions for large systems. Although, these methods are more flexible for handling various constraints, the solutions produced are suboptimal, and very sensitive to variations of the Lagrange multiplier value.

Recently, knowledge based approaches have been applied for generating satisfactory schedules with reasonable computing requirements [4]. These methods rely heavily on the use of domain knowledge. Use of heuristics allows inclusion of various constraints, but the solutions are generally far from optimum. More recently, stochastic search algorithms such as simulated annealing and genetic algorithms have been successfully used for generating globally optimal schedules [5, 6]. The main limitation of simulated annealing-based methods is the difficulty in tuning the control parameters. The genetic algorithm (GA) based approaches are found to be more suitable for generation scheduling problem. The performance of a GA depends on the scheme employed for encoding and decoding the binary solution strings. However, GAs have their own limitations for constrained optimization problems. The main limitation is that the majority of the population may remain far away from any feasible solution, resulting in inefficient search within the solution space and therefore, considerable waste of computer time.

This paper combines the advantages offered by heuristic approaches with the strengths of evolutionary computation [7], and presents an integrated framework for generating optimum unit commitment and dispatch schedules. Together, these two overcome the limitations of the approaches mentioned above. Heuristics is used to ensure that all constraint equations are fully satisfied in order for the solutions to be feasible, while the evolutionary algorithm works towards minimizing the objective function in order to obtain a high quality solution.

The Generation Scheduling Problem

Considering a power system of n fossil-fuel generators with an individual production cost C_i, expressed mainly as a function of its real power output P_{Gi}, the cost function can be modeled by the quadratic polynomial [1],

$$C_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \qquad (1)$$

where a_i, b_i and c_i are the cost coefficients of each generator i.

The objective function Θ to be minimized for minimizing the overall system cost is expressed as the sum of start-up cost (SU_i), shut-down cost (SD_i), hot-standby cost (HS_i), and running cost (equation 1),

$$\Theta = \sum_{i=1}^{n} C_i(P_{Gi}) + SU_i + SD_i + HS_i \quad \$/\text{h} \qquad (2)$$

The optimization of the above objectives is subject to the following constraints.

Power balance

The real power balance between generation and demand D must be maintained at all times.

$$D = \sum_{i=1}^{n} P_{Gi} \qquad (3)$$

Spinning reserve

For reliable operation, a sufficient amount of spinning reserve SR is required to be maintained at all times.

$$\sum_{i=1}^{n} (P_{Gimax} - P_{Gi}) \geq SR \quad (4)$$

where P_{Gimax} is the upper power limit of generator i. A very optimistic 10% daily peak risk of not meeting the demand in full has been used, so that an adequate, but not excessive, amount of generation can be ensured over the forecast demand curve.

Maximum And Minimum Output Limits On Generators

For stable operation, each operating unit should operate within its limits, thus imposing the inequality constraint on the individual upper and lower power output limits of each generator G_i,

$$P_{Gi\ min} \leq P_{Gi} \leq P_{Gi\ max} \quad (5)$$

Power Rate

The maximum rate of change of real power output is not allowed to exceed its rated value.

$$\nabla P_{Gi} \leq \nabla P_{Gimax} \quad (6)$$

Minimum Run Time

An operating unit G_i must operate for a specified minimum run-time T_{iu} before it can be brought off-line.

$$0 < T_{iu} \leq \text{Number of hours unit } G_i \text{ has been on-line} \quad (7)$$

Minimum down time

A unit G_i in down state can not be brought on-line before the elapse of its specified minimum down-time T_{id}.

$$0 < T_{id} \leq \text{Number of hours unit } G_i \text{ has been off-line} \quad (8)$$

Unavailability due to maintenance

A unit G_i under maintenance is not included in the commitment plan.

Crew constraints

Only one unit in an area can be started/shut down in any particular period.

An Integrated Approach

This paper aims to utilize heuristic approaches and evolutionary algorithms (EA) to arrive at an approach which performs an efficient global search of the feasible solution space. To accomplish this, the solution strategy starts with an evolutionary algorithm which utilizes a mating scheme

based entirely on the objective function which measures the quality of solution. Due to the presence of various constraints as described above, the new genotypes generated by mutation or recombination may not correspond to feasible solutions. This paper approaches this issue by using an indirect representation for solutions and by defining a decoding procedure that always generates a feasible solution.

A solution is indirectly encoded as a weight matrix, whose elements are floating point numbers between zero and one, associated with each unit for each hour of the day. A slightly modified heuristic algorithm previously proposed by one of the authors [8] is used to build a feasible unit commitment pattern given a weight matrix. Selection of the best unit for turn on/off, as well as the output of each unit, is based on these weights. The feasibility of the population is enforced by using heuristics which pays attention to the fulfillment of constraints. A local search is performed by the heuristic algorithm to obtain a highly fit offspring which is also a feasible solution. In this manner, the global search of evolutionary algorithm is combined with the local heuristic search to obtain an algorithm which efficiently searches the feasible solution space.

The algorithm is implemented as a stead-state EA. The population is seeded with randomly generated individuals. The algorithm is summarized in Fig. 1, where u represents an integer random variable with uniform distribution on {1, ...,*popsize*}.

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initialize population *pop*[1,....,*popsize*];
repeat
    mother = winner(*pop*[u], *pop*[u]);
    child = looser;
    if crossover **then**
        father = winner(*pop*[u], *pop*[u]);
        child ← mate(*father, mother*);
    else
        child ← *mother*;
    mutate (*child*);
until termination.

Fig. 1: Pseudocode for the algorithm

In this hybrid framework, the search process can be halted at virtually any point and return a useful solution. The algorithm iteratively improves a set of feasible, but initially suboptimal schedules, until an optimum solution is found, an arbitrary bound on the number of generations is reached, or the user terminates the search.

Implementation and Results

Experiments were carried out with three test systems of small medium and large size, comprising respectively of 11, 19 and 40 thermal units. The algorithm was tested for obtaining generation schedules for different load curves and initial conditions for each problem. For each test problem, the EA ran for 400,000 steps, with population size of 200, crossover rate of 60% and mutation rate of 1% on an HP 712/60 workstation.

Due to space limitations, the data for 11-unit system only is given here (Table I). A summary of results obtained for the three problems is presented in Table II. It should be noted here that the execution times vary almost linearly with the size of the problem. This is a significant advantage over most of the conventional techniques used for this problem, where the execution time and memory requirements increase exponentially with the number of units considered.

Table I
Data for the 11-unit system

Unit	Type	P_{max}	P_{min}	T_{iu}/T_{id}	HS_i	SU_i	a_i	b_i	c_i
1	coal	250	120	3/6	252	5266	220.50	7.07	0.00032
2	coal	250	120	3/6	252	5266	220.50	7.14	0.00036
3	oil	120	60	1/3	384	2723	109.60	16.00	0.00230
4	oil	120	60	1/3	384	2723	109.60	16.00	0.00230
5	oil	120	60	1/3	389	2805	51.81	16.62	0.00290
6	oil	120	60	1/3	389	2805	51.81	16.71	0.00290
7	oil	120	60	1/3	389	2805	51.81	16.78	0.00290
8	gas	60	20	0	0	120	81.70	18.22	0.03890
9	gas	60	20	0	0	120	81.70	18.28	0.03890
10	gas	60	20	0	0	120	74.31	18.01	0.03450
11	gas	60	20	0	0	120	74.31	18.00	0.03450

Table II
Cost and execution times for the test problems

Number of units	Minimum cost solution ($)	CPU Time (sec)
11	266919.125	276
19	428973.125	481
40	1078182.25	1016

Conclusion

Given limited computational resources and a complex environment, the solution strategy presented here aims to use heuristics to generate a population of feasible schedules and use an evolutionary algorithm to find globally optimal schedules. This approach searches the feasible solution space more efficiently than pure genetic algorithm based approaches. The main advantage derived by restricting the population to the set of feasible solutions is substantial savings in computer time. In addition, the offsprings tend to inherit those features from each parent which optimally contribute to its fitness, therefore, this algorithm is likely to find high quality solutions sooner than the one which depends entirely on natural selection. Experimental results on three test systems indicate that the algorithm performed as predicted, producing high quality results in reasonable execution times.

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