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Generation Scheduling using Genetic Algorithm based Hybrid Techniques

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***Abstract*-- The solution of generation scheduling (GS) problems involves the determination of the unit commitment (UC) and economic dispatch (ED) for each generator in a power system at each time interval in the scheduling period. The solution procedure requires the simultaneous consideration of these two decisions. In recent years researchers have focused much attention on new solution techniques to GS. This paper proposes the application of a variety of genetic algorithm (GA) based approaches and investigates how these techniques may be improved in order to more quickly obtain the optimum or near optimum solution for the GS problem. The results obtained show that the GA-based hybrid approach offers an effective alternative for solving realistic GS problems within a realistic timeframe.**

***Index Terms*-- Unit commitment/Economic dispatch, Genetic algorithm, Hybrid approach.**

I. INTRODUCTION

THE solution of generation scheduling (GS) problems involves the determination of the unit commitment (UC) and economic dispatch (ED) for each generator in a power system at each time interval in the scheduling period [1],[2]. UC decides which of the generating units are on or off in each time interval of the scheduling horizon and ED determines the allocation of the power output (system load) to the generating units. The solution of GS problems requires the simultaneous consideration of these two decisions. Of course, this is one large problem, manifesting itself mathematically as a mixed-integer-programming problem. However, historically it was regarded as two separate problems, largely because of the complexity of the combined problem. In general, GS problems are highly constrained and combinatorial in nature, and continue to present a challenge for efficient solution techniques [1], [2]. In the open energy market environment the GS problem can be even more complex requiring a whole range of financial and technical issues to be addressed in the solution process [3].

A variety of different techniques have been employed to solve the UC/ED problem [1]. Mathematical programming techniques work efficiently and obtain the optimal solution for problems with small dimension under certain conditions and assumptions. However, these approaches are severely limited by the 'curse of dimensionality' and are poor in handling the nonlinear objective functions and constraints that typically characterize the GS problem [4]. Therefore, very often the solution of such scheduling problems is approached by heuristic-based methods and expert systems [1]. In general these approaches use a trial-and-error method to meet objectives in the time interval under examination. The tendency is to consider each generating unit separately and consequently, these methods cannot guarantee the optimal solution. Expert systems generally require a lot of operator interaction. Furthermore, solution approaches of these types are based on specialized techniques that work particularly well for a given problem but are only of limited applicability to other problems [1].

In recent years researchers have focused much attention on new solution techniques to GS [2], [5]. This paper proposes the application of a variety of genetic algorithm (GA) approaches for solving the GS problem. The main disadvantage of the GA approach is often a large computational time [6]. This paper investigates how GAs may be improved in order to more quickly obtain the optimum or near optimum solution. Five GA-based approaches, from a simple GA to a hybrid GA, are developed and studied for a test GS problem. Although the proposed techniques can be adapted to tackle GS problems in the open energy market environment, in this paper the application of these approaches are demonstrated for a centralized GS problem. The results obtained show that the GA-based approach offers an effective alternative method for solving realistic GS problems within a realistic timeframe. The paper is organized as follows. Section II describes the general GS problem and the test case study. Section III discusses the proposed GA approaches, their implementation and the results obtained. The conclusions are noted in Section IV.

II. PROBLEM DESCRIPTION

A. Problem statement

The GS (UC/ED) problem is a short-term scheduling problem, typically with a scheduling period of twenty-four hours. The main objective of a centralized GS problem is to minimize the total cost of power generation in a power system over the scheduling period [1]. The total cost of generation depends on the operating, start up and shut down costs of the individual generating units, summed over all units and time intervals. This is subject to a variety of operational constraints. The total generation must meet the forecast demand and

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network losses; moreover there must be a certain level of reserve capacity available. Individual generating units are characterized by constraints including the minimum and maximum generation levels, ramp rate limits on the increase and decrease in generation, and the minimum up and down times. There may also be limits on the generation within local areas. The objectives and typical constraints of the GS problems are characterized by non-linear, multi-model and discrete functions.

B. Test case study

For demonstration clarity a small test problem involving five generating units and six four-hour time periods is considered. The problem is to schedule the generation of each generating unit for each time period. This test problem is taken from the example presented in [7] and has been designed to incorporate some of the characteristics of larger systems. The test problem provides a simple benchmark for demonstrating the application and analysis of the application of GA-based approaches. Data for the test problem is given Table I. The reserve capacity of the power system is required to be greater than or equal to 200 MW. Local area constraints require that the sum of the generation of generating units 1 and 2 minus the sum of the generation units 3, 4 and 5 must be within the range of [-200MW, +200MW]. The MW demands (including losses) for the six time periods are: 1000, 1680, 1600, 1840, 1600 and 1200.

TABLE I
RELEVANT DATA OF GENERATING UNITS.

Unit	Min gen. (MW)	Max gen. (MW)	Fuel cost units/MWh	No-load cost units/hr	Start-up cost
1	130	500	2.5	125	1250
2	250	500	2.0	200	1500
3	165	660	1.0	132	6600
4	50	200	3.0	120	900
5	0	340	6.0	102	204

To avoid the complication of initial and final conditions, a cyclic boundary condition is adopted. This boundary condition means the sequence of events is assumed to repeat indefinitely (the first time step follows the last).

C. Optimum solution

This GS problem can be formulated as a mixed integer-programming (MIP) problem [7] with binary commitment and start-up variables, and continuous generation dispatches variables. Although the general GS problems are inherently nonlinear in nature, the objective and constraints of the test problem can be formulated with linear functions. This linear MIP can then be solved using the branch and bound (B&B) technique. This linear MIP problem has been solved using the AMPL programming language with OSL solver routines [8]. The optimum solution of the problem found by the solver is given in Table II, and has a total cost of 76172 units. The time taken by the branch and bound method is 1.4s. This however, is not applicable to large-scale problems as the computational time increases prohibitively with the problem size.

TABLE II
OPTIMUM SOLUTION OF THE TEST PROBLEM.

	Generating units				
Periods	1	2	3	4	5
1	130	270	600	OFF	OFF
2	440	500	660	80	0
3	390	500	660	50	OFF
4	500	500	660	180	0
5	390	500	660	50	OFF
6	130	410	660	OFF	OFF
Cost	76172				

III. PROPOSED GA APPROACHES AND TEST RESULTS

A. GAs and implementation

GAs are search and optimisation methods based on a model of evolutionary adaptation in nature [5],[6]. Unlike traditional ‘hill-climbing’ methods involving iterative changes to a single solution, GAs work with a population of solutions, which is ‘evolved’ in a manner analogous to natural selection. Candidate solutions to an optimisation problem are represented by chromosomes, which for example encode the solution parameters as a numeric string. The ‘fitness’ of each solution is calculated using an evaluation function which measures its worth with respect to the objective and constraints of the optimisation problem. A new 'generation' of the population is created by stochastic operators - typically ‘crossover’, which swaps parts of solution strings (chromosomes), and ‘mutation’, which changes random bits in the strings. Relatively ‘fit’ solutions survive, ‘unfit’ solutions tend to be discarded. Successive generations yield fitter solutions, which approach the optimal solution to the problem. The creation and evaluation of a large number of solutions can be computationally costly [6].

Here we propose a number of GA designs, from a basic GA to an advanced hybrid approach, in order to improve their performance and the computational time to obtain the optimum or near optimum solution for the GS problem. For all of these GA designs a binary string has been adopted to represent candidate solutions of the UC/ED problem [9]. A penalty function approach has been used to take account of the constraints for the test problem [10]. The penalty value for each constraint violation is proportional to the amount by which the constraint is violated. The evaluation function is the weighted sum of penalty values for each constraint violation and the objective function itself.

The particular GA parameters (population size, number of generations, crossover probability and mutation probability) that give the best performance for each of the proposed approaches have been identified after a process of experimentation. The general approach adopted during the tests of each of the GA designs was to conduct ten runs until the stopping criterion (a given number of generations) is reached. The best solution obtained, computational time for one run and mean computational time to obtain the optimum solution (if found) were recorded for each of the proposed GA designs (see Table III later). The different GA designs have been implemented on a Sun Sparcstation 1000 using the Reproductive Plan Language, RPL2 [11].

The following subsections outline aspects of the alternative GA designs used in the experimentation. A more detailed description of these alternatives is available in [4], [7], [12].

B. *Two stage GA*

A two-stage GA approach is proposed to solve the GS problem. Firstly, the UC problem is solved taking into account the full output of generators for each time period. Secondly, using the obtained UC results, the dispatch variables (ED) are determined. GAs are used for both stages.

In the first stage GA a binary string has been adopted to represent candidate solutions of the UC problem. The string uses thirty binary bits to represent the commitment variables for the five generators over the six time periods of the test problem. Ten of the best UC solutions given by the fist stage GA have been forwarded to the second stage of the algorithm.

In the second stage the output of each committed unit is identified for the best ten commitment decisions obtained in the first stage using an independent GA. A binary string is used to encode the dispatch variables of the ED problem. A five bit-string is set for each committed generator in each time period. With this approach the length of a GA string varies according to the commitment decisions. The maximum length of a single string for this test problem is 150 bits.

The best solution found by the two-stage GA approach has a cost value of 76328. The computational time taken by one run of the first stage GA was typically thirty seconds. One run of the second stage GA to calculate dispatch variables for one set of UC variables took about seven minutes, i.e. for the ten sets of the UC it took about seventy minutes. This is very laborious and time consuming and could not be used for large problems without an improvement.

C. *Explicit GA*

An attempt at encoding both the UC and ED between committed units in a single GA is here referred to as an explicit GA. A problem representation has been designed using a binary string which includes binary sub-strings for each unit at a scheduling period. A sub-string containing six bits has been used to represent a generating unit at a particular time period. Of the six bits, one bit represents commitment and the remaining five binary bits indicates the ED variable of the unit for that time period.

The computational time taken for a run of the GA was approximately eight minutes. The explicit GA has been able to find the optimum UC decision for the problem. This approach however, could not find the optimum values of the dispatch variables. The best solution found by the explicit GA has a cost value of 76232.

Unlike the two-stage GA approach, the explicit GA incorporates both the UC and the ED problem during the solution process and solves this as a single problem. The computational time required for the explicit GA, however, is very large (about eight minutes) given the size of the problem.

D. *Integrated GA*

The proposed integrated GA decomposes the scheduling problem into UC and ED problems. Fig. 1 shows the structure of the integrated GA for solving the GS problem.

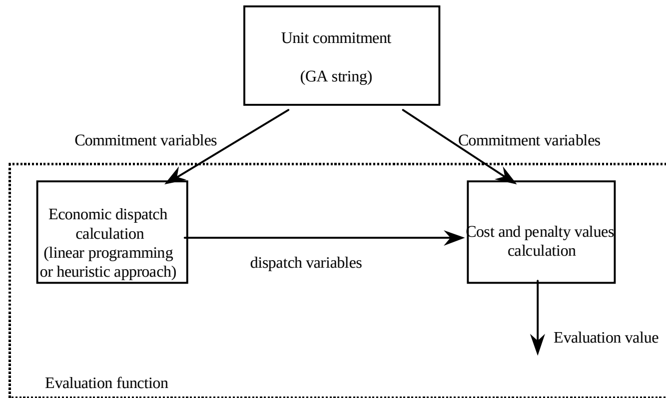

Fig. 1: Structure of the integrated GA approach.

The UC problem is an integer problem and is represented in the GA solution string as a binary array as in the two-stage GA. The combinatorial aspect of the UC problem is a natural target for the application of GAs. The ED problem is a real number (continuous) problem and can therefore be solved as part of the evaluation value calculation as indicated in Fig. 1. During the calculation of the evaluation measure of each string first a linear program (LP) ED is formed for the given commitment decisions and the LP is solved to give dispatch variables. Secondly, the evaluation value is determined from the total cost plus a weighted sum of penalty functions. This takes into account infeasibility of the LP problem. AMPL with OSL solver routines [8] has been used to solve the LP problem. The routine returns a minimum sum of infeasibility when presented with an infeasible problem.

All ten GA runs with this design found the optimum solution. The computational time taken for a run of the integrated GA was approximately five minutes. The computational time required for the integrated GA is still large given the size of the problem. If we compare this with the computational time (about half a minute) required for the GA to solve only the UC problem, we conclude that most of the computational time of the integrated GA is taken by the LP (ED) problem. Improvements to this part of the problem were therefore sought.

E. *GA-heuristic hybrid*

The proposed GA-heuristic hybrid approach employs a heuristic method for calculating dispatch variables for the given commitment decisions rather than the aforementioned standard LP solver as part of the evaluation value calculation. In this heuristic method at each time interval the dispatch variables are successively adjusted, using merit order, in order to satisfy the group constraints and demand. This is achieved by applying heuristics which take into account the values of dispatch variables at previously set times, the given commitments, and the unit capacities and ramp-rates. This approximate method proved to be a fast and sufficiently accurate alternative to the exact LP method to obtain the optimum commitment.

The hybrid was run for ten experiments. With this approach the computational time taken by this approach was reduced dramatically. One run of the GA-heuristic hybrid took about 40s. The best solution found by the GA-heuristic hybrid approach has the cost value of 76792. The best solution given by this approach is close to the optimum solution, and though the evaluation function is approximate, the optimum commitment is consistently found.

F. Knowledge-based hybrid GA

The GA approach explained in the previous section may be further improved by hybridizing it with other approaches for refining the candidate solutions before and/or after a GA process. A knowledge-based hybrid GA is proposed by adopting the GA-heuristic hybrid approach with a pre-GA and post-GA process for the GS problem.

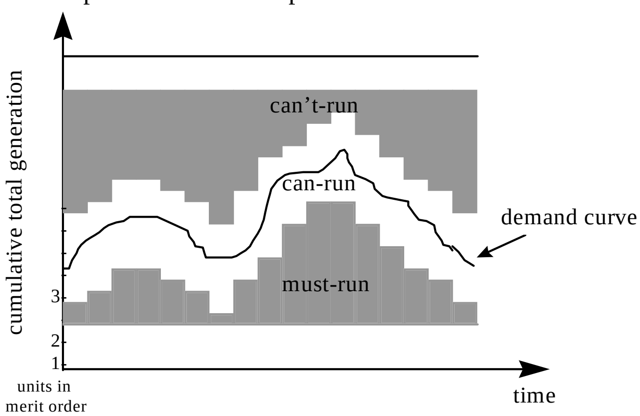

Fig. 2: Partitioning of generating units.

For the pre-GA process, a partitioning approach was employed to identify the likely structure of the unit commitments. The units are initially placed in merit order (here in order of average running cost/MWh at full output), and their cumulative total generations calculated. Units which lie sufficiently below the minimum demand are classified as "must-run"; units which lie sufficiently above the maximum demand are classified as "can't-run"; and those remaining are "can-run" units. This allocation is indicated for representative load curve in Fig. 2. The partitioning is realized through implementation of expert knowledge. The resulting 'partition' is then used to initialize the population of the GA. The partitioning technique employed to seed the initial population for the reported test problem uses a margin around the demand curve of ±500 MW.

For the post-GA refinement, an LP approach is employed to recalculate the exact ED solution to the best commitment decisions obtained from the GA. Again AMPL with OSL solver routines has been used to solve the LP. However unlike the integrated GA, the LP in the knowledge-based hybrid GA is solved only once for the best commitments given by the GA. As before the evaluation value calculation employs the approximate heuristic method to determine the ED variables. A total of ten experiments have been performed with different seeded initial populations using the partitioning approach. The computational time taken by one run of the GA was about 45s. All ten experiments located the optimum solution with the mean computation time of 14s.

G. Comparison of different GA approaches

Table III summarizes the results obtained using the different approaches described in the previous sections. This table shows the cost of the best solution found, the computational time for the given number of iterations and the mean computational time to find the optimum solution.

TABLE III
RESULTS OBTAINED FROM DIFFERENT APPROACHES.

Techniques	Cost of best sol.	Comp. time	Mean comp. time to opt.
Branch-and-bound	76172	1.4s	1.4s
Two stage GA	76328	4230s	Optimum not found
Explicit GA	76232	480s	Optimum not found
Integrated GA	76172	300s	96s
GA-heuristic	76792	40s	Optimum not found
Knowledge-based hybrid GA	76172	45s	14s

In the two stage GA approach the solution requires the best set of UC solutions, rather than just the best one, from the first stage as a template for the dispatch in the second stage. Although the first stage GA requires about 30s to solve the UC problem, the overall approach is quite time consuming and therefore is inappropriate for application to larger problems.

The explicit GA is also a time consuming approach and therefore is unsuitable for larger problems without significantly improving its speed. Comparing the computational time (30s) required for the GA to solve only the UC problem, it is obvious that the large computational time required for the explicit GA is due to the inclusion of the ED variables in solution strings.

The integrated approach has been able to find the optimum solution with a computational time of 300s. Here the LP problem was solved exactly by using the LP solver to find the exact solution to the LP problem. It is obvious again that most of the computational time is taken by the LP solver, making the integrated approach still a computational costly method.

The GA-heuristic hybrid found the optimum commitments for the problem, but the exact optimum values for the dispatch variables were not found.

The results presented in Table III show that the knowledge-based GA approach gives the best performance in terms of the cost of the best solution found and the computational time taken, compared with the other GA-based approaches. However, the B&B technique found the optimal solution for the test problem considered in 1.4s. The computational time for the B&B technique however, increases prohibitively as the size of problem increases. Furthermore, it cannot readily be applied to problems with nonlinear objectives and constraints.

The knowledge-based GA has also been tested on a larger non-linear problem and has been found effective in comparison with the Lagrangian relaxation technique. This is discussed in more detail in [4], [12]. This approach offers an effective alternative method for solving realistic GS problems within a realistic timeframe.

IV. CONCLUSIONS

The paper has investigated the application of a variety of GA approaches for solving the generation scheduling (Unit commitment/economic dispatch) problem in power systems. Five GA-based approaches namely; a two stage GA, explicit GA, integrated GA, GA-heuristic hybrid approach and knowledge-based hybrid GA have been developed and studied for the UC/ED problem.

The two-stage GA solves the UC problem by first considering full unit capacity and then solves for the ED variables for the best UC result obtained. The explicit GA encodes both UC and ED problems in the solution string. The integrated GA encodes only the UC problem in the solution string and solves the ED problem within the evaluation value calculation using a linear programming (LP) method. In the GA-heuristic hybrid method the ED is solved by using a heuristic approach to calculate dispatch variables. This calculation is approximate, however it requires much less computational time compared with that required for the LP method. The knowledge-based hybrid GA uses the GA-heuristic hybrid approach with pre- and post- GA processing.

The results obtained show that the knowledge-based hybrid GA approach is an effective choice for the solution of the GS problem. In this approach, each binary string is a complete commitment schedule, and the corresponding dispatched generations are determined in the evaluation value calculation of each string. Domain knowledge of GS is used to define the initial conditions of the GA. This has been shown to make the method more consistent in finding the optimum solution. Scheduling rules are incorporated in a fast approximate method of evaluating solutions, accelerating the computational time of the GA to competitive levels. The results obtained show that the knowledge-based hybrid approach offers not-inconsiderable advantages over these alternative formulations. Whereas it is computationally slower than a classical branch-and-bond solution for the small test system described, results have been shown that it does not suffer the same rate of slow-down as the problem grows - it is therefore more suited to realistic problems.

V. ACKNOWLEDGMENTS

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VII. BIOGRAPHIES

Dr Keshav Dahal received an MSc in Electric Power Systems from Belorussional Polytechnical Institute in 1991, and an MSc in electrical power engineering in 1995 and a PhD in 2000, both from the University of Strathclyde. His research interests lie in the areas of evolutionary computation, scheduling and optimisation, power system modeling, electricity market modeling and discrete event simulation.

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