A HEURISTICS-GUIDED EVOLUTIONARY APPROACH TO MULTI-OBJECTIVE GENERATION SCHEDULING

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ABSTRACT

A novel approach for multi-objective generation scheduling is presented. The work reported here employs a simple heuristics-guided evolutionary algorithm to generate solutions to this nonlinear constrained optimization problem where the objectives are mutually conflicting and equally important. The algorithm produces a cost-emission frontier of Pareto-optimal solutions, any of which can be selected based on the relative preference of the objectives. Within this framework, an efficient search algorithm has been developed to deal with the combinatorial explosion of the search space such that only feasible schedules are generated based on heuristics. This approach has been evaluated by successful experiments with three test systems containing 11, 19 and 40 generating units. Attaching importance to heuristics results in producing high-quality solutions in a reasonable time for this large-scale tightly-constrained problem.

I. INTRODUCTION

The primary objective of current day operation planning is to ensure the availability of adequate generating margins, in excess of estimated load levels over the entire planning horizon, while respecting various operating constraints. To achieve this, optimum generation schedules need to be determined to find the commitment pattern and power allocation of each generator in this scheduling period.

The generation scheduling problem is a large nonlinear mixed integer programming problem with a large number of decision variables. The approaches to solve the generation scheduling problem vary with respect to the methodology used, the objectives considered, and constraints included in the formulation. Although many methods have been developed for solving this problem with minimization of cost as the main objective [1, 2], their applicability to large systems is questionable. The optimization-based solution methods, such as, dynamic programming, Lagrangian relaxation, integer programming and Benders decomposition make several assumptions to make the problem solvable using realistic computational resources. Recently, stochastic search methods such as simulated annealing and genetic algorithm (GA) have been applied and found to be successful [3 - 5].

The rising awareness regarding the environmental aspects of electricity generation has necessitated a shift from the narrower, purely economic approach currently in practice. Evidently, effective operating policies need to be determined using a comprehensive framework that fully takes into account the economic-environmental interactions. A reduction in the emissions from fossil fuel plants can be achieved by conducting the optimization algorithm such that the total emissions are minimized. In this manner, generating units emitting large quantities of pollutants would generate less than they would under a minimum-cost solution. Other methods to reduce emissions include use of special cleaning systems to arrest pollutants, and switching to cleaner fuels [6]. Since all these methods impose additional economical burden, it is clear that a reduction in emissions can only be achieved at an additional cost.

In practice, evaluation of trade-offs between economic and ecological factors is a very difficult task. The main factor complicating the process is that benefits cannot be easily expressed in monetary terms for a direct determination of trade-offs in relevant physical quantities. The optimization techniques currently in practice do not provide a convenient way to solve this type of multi-objective problems. For this reason, instead of treating cost and emission as competing objectives, most of the approaches express the maximum allowable emission rates as constraints in the formulation of unit commitment and economic dispatch problems [6]. Another method for finding a compromise solution using conventional techniques converts the multi-objective problem into that with a single objective by assigning relative weights to each objective [7]. Fuzzy multi-objective optimization technique developed in [8] efficiently handles multiple objectives, but the solutions produced are sub-optimal, and the algorithm does not provide a systematic framework for directing the search towards optimal solutions.

This paper presents a novel approach for solving the generation scheduling problem by simultaneously optimizing the operating cost and emissions. The work reported here employs the techniques of evolutionary computation, which has been regarded as one of the most promising approaches to solve this type of optimization problems because of its efficient handling of multiple objectives and constraints. The principle and algorithm of the proposed method are presented in this paper. The emphasis has been placed on the necessity to make the work easy for the control center operators in determining optimum generation schedules. The optimization is done over the entire planning horizon of 24-hours, based on the system daily load curve. The results obtained for three test systems containing 11, 19 and 40 thermal generating units have been presented. The approach presented here has the following distinguishing aspects:

1. This approach finds multiple near-optimal solutions to the problem involving multiple conflicting objectives.

2. Use of heuristics results in producing high-quality solutions in a reasonable time for a large-scale tightly-constrained problem.

3. Computing the optimal multi-step schedule, for the entire scheduling horizon of 24 hours, leads to faster solutions because it avoids the expense of computing optimal single-step solutions for each hour separately, and then obtaining the overall multi-step optimal solution.

4. The proposed scheme works only with feasible solutions, which are generated based on heuristics, thus avoiding the computational burden entailed by other methods which first generate all the solutions and then purge those that are infeasible.

5. The solution time increases almost linearly with the number of units, thus making the approach suitable for large-scale problems. Another important aspect of the algorithm is that the solution time remains the same irrespective of the number of objectives considered.

II. AN EVOLUTIONARY ALGORITHM

This section describes an Evolutionary Algorithm (EA) for the multi-objective generation scheduling problem. EAs have already been applied with success to multi-criteria optimization problems (for an example in Finance see [9]) and a body of theoretical work has been produced [10, 11]. The one described below is a novel approach to multi-objective optimization, based on competitive selection [12].

The name *Evolutionary Algorithm* encompasses a family of stochastic optimization techniques based on the key concept of *evolution*. The first proposals in this direction date back to the mid sixties, when John Holland introduced Genetic Algorithms [13] and Ingo Rechenberg and Hans-Paul Schwefel independently began to work on Evolution Strategies. Their pioneering work eventually gave rise to a broad class of optimization methods particularly well suited for

hard problems where little is known about the underlying search space. A recent work of reference and synthesis in the field of EAs is [14].

An EA makes a population of appropriate representations, also called *genotypes*, of candidate solutions to the problem at hand (*phenotypes*) evolve by iteratively applying a set of stochastic operators, known as *mutation*, *recombination*, *reproduction* and *selection*. Mutation randomly perturbs a candidate solution; recombination decomposes two distinct solutions and then randomly mixes their parts to form a novel solution; reproduction replicates the most successful solutions found in a population, whereas selection purges poor solutions from a population.

The resulting process tends to find globally optimal solutions to the problem much in the same way as in *Nature* populations of organisms adapt to their surrounding environment.

III. MULTI-OBJECTIVE GENERATION SCHEDULING

The task of finding optimum generation schedules has no unique solution if the objectives are conflicting and equally important. There is an infinite number of *Pareto-optimal* solutions, which complicate the decision-making process. Multi-objective generation scheduling can thus be viewed as a complex combination parametric programming problem [15], where the performance indices to be minimized constitute the mutually conflicting objective functions.

In this setting, minimizing an arbitrary combination of these objectives, while perhaps justifiable from a practical standpoint, is by no means satisfactory, in that it commits the solution to a particular trade-off among the objectives. On the other hand, for the human decision-maker confronted with critical choices it is much more helpful to be supplied with a whole range of alternative solutions. Each one of these solutions is guaranteed to be Pareto-optimal, that is non-dominated, in that there are no other solutions superior in all attributes. In the attribute space, the set of these non-dominated solutions lie on a surface known as the *Pareto optimal frontier*. Based on the relative preference of these objectives, any of these solutions can be chosen by the operator.

In generation scheduling problem, there exist many objectives, such as economy, emission, security, and reliability, each equally important but with unique characteristics. In addition, these objectives cannot be accurately expressed mathematically for a direct comparison in terms of their performance indices. The present work treats economy and emission as the conflicting objectives for the generation scheduling problem. These objectives are formulated as follows [8].

Economy

The fuel cost of a power system consisting of *n* generators each with individual production cost C_i expressed mainly as a function of its real power output P_i can be modeled by the quadratic polynomial [16]

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i \qquad (1)$$

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

The objective function O_1 to be minimized for optimization of the overall system cost is expressed as the sum of the running cost (1), the total start-up cost (SU_i), shut-down cost (SD_i), and the hot-standby cost (HS_i). The last three variables are non-zero only for those units started/shut down/kept hot-standby in that particular hour.

$$O_1 = \sum C_i(P_i) + SU_i + SD_i + HS_i \qquad \$/h \tag{2}$$

Emission

In a power generating system containing fossil-fuel units, the total emission can be reduced by minimizing the four major pollutants - oxides of nitrogen (NO_x), oxides of sulfur (SO_x), carbon dioxide (CO_2) and particulates. The objective function that minimizes the total emissions can be expressed in a linear equation [6] as:

$$O_2 = \sum E_i P_i \quad \text{tons} \tag{3}$$

where E_i is the sum of all the four pollutants (in tons/MWh) resulting from generation P_i of the i^{th} generator. Although, equation (3) above gives equal importance to various pollutants, it can be easily modified to attach different weights to them.

The schedule is obtained considering the following constraints:

Unit operating constraints - Minimum up and down times, ramp rate limits, minimum and maximum output limits, unavailability of a unit due to planned maintenance or forced outage. In addition, plant crew constraints are also included in the formulation.

Generation and reserve constraints - Ignoring transmission losses, the total generation from all on-line units must equal the load demand. A 10% spinning reserve over and above the demand is required to be maintained at all times in order to meet random disturbances and to ride through contingencies.

IV. ALGORITHM OVERVIEW

Multi-objective generation scheduling is a highly constrained problem and, as such, it poses a special challenge to EAs, in that new genotypes generated by mutation or recombination may not correspond to feasible solutions. The present work addresses this problem by using an indirect representation for solutions and by defining a decoding procedure that always generates a feasible solution. This is done by encoding the solution as a weight matrix, whose elements are floating point numbers between zero and one, associated with each generating unit for each hour of the day.

In this problem, searching the space of all possible schedules exhaustively for each hour is prohibitive, a practical approach to the problem of cost-effective scheduling is still possible within the framework of heuristic search. Many action sequences are implausible or counterproductive, either because actions lead away from the goal or because they do not satisfy the constraints. By using heuristics, the space of possible action sequences can be searched intelligently in order to find a good, if not optimal, multi-step schedule for the entire planning horizon of 24 hours. The selection procedure employed by the evolutionary algorithm estimates the relative merit of different sequences, and ensures that the final schedule will be superior in all respects.

The algorithm implemented is a steady state EA, and is described in the following steps (Fig. 1).

Initialization

The parameters of the evolutionary algorithm are initialized by seeding the population with randomly generated individuals, which are weight matrices of dimension [number_of_units X number_of_hours]. The other inputs to the algorithm are generating unit data, initial conditions, and the daily load curve.

Decoding vectors using heuristics

A slightly modified version of the heuristic algorithm developed by one of the authors in [13] is used to build feasible unit commitment pattern given a weight matrix. Selection of the best unit for turn on/off, as well as the output assignment of each unit, is based on these weights. This algorithm can be summarized as follows.

For every hour, the load demand from the load curve, and the previous hour's generation schedule is obtained. An initial solution for the current hour is then obtained by multiplying the components of the weight matrix at that hour for each unit by its maximum output limit.

The initial schedule obtained above may have violated the minimum power output constraint, power rate constraint or minimum up and down time constraints for some units. Based on these, the initial schedule is modified to include only those units that satisfy all the constraints. Note that the maximum power output limit constraint is never violated, since the unit outputs are obtained by multiplying this limit with the corresponding element in the weight matrix which have a maximum value of 1.0.

The next step is to check if the power balance constraint is met.

> In case of a deficiency, the best unit for start-up is searched for based upon the numbers in the weight matrix. For this, the weight matrix elements of all off-line units are arranged in descending order, and the units are successively picked until the deficiency is fully met. Heuristics is used to make sure that all constraints are observed.

In case there is a surplus, the best unit or a combination from all the on-line units is searched for based on the elements in the weight matrix, arranged in ascending order. The unit with the smallest element is decommitted first. As above, if any constraints are violated, the unit is deemed unsuitable and the next best candidate is considered. The process is repeated until the surplus has its smallest possible non-negative value.

Once the power balance requirement is satisfied, a final check against all the unit operating constraints is made. If a constraint is violated for any unit, its output is fixed at the limit, and the outputs of all other on-line units are re-adjusted by uniformly distributing the resulting inequality in the power balance equation.

For including the spinning reserve constraint, the power balance equation is modified to include a 10% reserve, while the power output calculation for each unit remains the same as above.

Evaluation of objective functions

The result of this decoding is a matrix of dimension [number_of_objectives] containing the values for each objective function, over the scheduling horizon of 24 hours, based on the generation schedule generated at the above step. Equations 2 and 3 are used for this calculation.

Formation of mating pool

Two individuals are randomly selected from the population and a stochastic competition is performed to find the winner. For this, the two individuals are compared according to any one objective (economy, emission, etc.) selected with uniform probability. The winner is the one having the least value for that objective.

To ensure a uniform covering of the Pareto-optimal frontier, a non-dominated individual can never be replaced by a dominated one. The winner thus found receives a copy in the mating pool. This process is repeated until the size of the mating pool is the same as the population (pop-size).

Crossover, mutation and selection

Crossover Recombination is implemented through uniform crossover, whereby each component of the off-spring genotype is randomly selected from either parent with equal probability and independently of other components. Uniform crossover has the nice characteristic of being unbiased with respect to the disposition of genes in the genotype [18].

Mutation The least elaborate of all mutations has been employed: every time genetic material is copied from an existing individual to a new one, each component of the weight matrix has independent and identical probability of being corrupted, that is, of changing to a new random value uniformly distributed on the interval [0, 1].

Selection A particular version of binary tournament selection has been employed, relying on a stochastic function which, given two competing individuals, chooses a winner according to a probability [12]. This allows the algorithm to do without the explicit definition of a fitness function, which in this case would be difficult to form and would involve arbitrary choices, given the need of composing two conflicting objectives.

The off-springs evolved through the processes of crossover, mutation and selection are weight matrices of dimension [number_of_units X number_of_hours]. The above processes are repeated until the number of these off-springs equals the pre-defined population size.

The old population is replaced with this new population of candidates and the above process is repeated until the number of generations reaches a pre-defined maximum value. As the evolution progresses, the algorithm generates the optimum set of weights which lead to non-dominated solutions. The final solutions are decoded using heuristics, as described above.

V. IMPLEMENTATION AND RESULTS

The approach presented has been tested by applying EA to three problems of different size, taking into account the two conflicting objectives of cost and emissions. Experiments were carried out first with three test systems (called Problem 1, 2 and 3) of small, moderate and large size, comprising respectively of 11, 19 and 40 fossil fuel units. The emission levels of the generators considered in these systems are given in Table I. The total emission index d_i of each unit is calculated as the sum of these pollutants, in tons/MWh. The algorithm was tested for different load curves and initial conditions for each problem. Due to space considerations, the detailed results for only Problem 1 are presented here. The data for this problem is given in Table II.

The algorithm was implemented on an HP 712/60 workstation. For each test system, the EA was allowed to run for 100,000 steps, with population size of 200, crossover rate of 60% and mutation rate of 1%. Fig. 2 shows a population of 200 individuals for Problem 1, upon termination of a run, plotted in two-objective performance space. It can be observed how the solutions are more or less uniformly distributed along the Pareto-optimal cost-emission frontier. Similar solutions were obtained for Problem 2 and 3.

A summary of results obtained for the three problems is given in Table III. The results obtained for the conventional single objective case are also shown, where objective is to optimize cost alone. The CPU times are identical for both single and two objective versions, since at each step only one of the randomly selected objectives is used for competition. The single objective versions achieved better solutions with regard to cost, as expected, since they could concentrate all the search effort on that objective only. It should be noted here that the CPU time increases almost linearly with the problem size.

Comparison with previous works

In order to evaluate the proposed approach against other contributions of the same kind found in the literature; two recent works were selected [4, 5], also utilizing evolutionary techniques

for generation scheduling. Another piece of interesting work described in [3] finds only the single-step optimal solution. A comparosin of performance with this work couldn't be made due to the incompleteness of the data. Since both works in [4, 5] took a single objective into account, comparison has been restricted to that case only, adopting the same performance indices.

The results of this comparison are summarized in Table IV, where the CPU times refer to the algorithm presented in this paper. The proposed heuristics-guided algorithm has performed better both in terms of cost and computing time, which is reported to be several hours for [4] and [5].

VI. DISCUSSION

The approach proposed in this paper exploits the advantages offered by a powerful optimization technique, evolutionary algorithm, to solve the multi-hour generation scheduling problem with multiple objectives. The algorithm starts with randomly generated matrices of weights which determine the unit commitment and generation dispatch schedules at each hour. These matrices are evolved during computation such that the solutions obtained after decoding are non-dominated.

The hourly schedules are generated using heuristics in the internal cycle. This algorithm uses a constrained based search, which involves finding a sequence of operations such that the goal is found following the most efficient path while no constraints are violated. Although evaluating all possibilities is intractable, use of heuristics guides the initial search and resolves local conflicts. In this way one is able to take advantage of available expert knowledge while preserving the generality of EA's search strategy.

Within this framework, the efficient search algorithm used here deals with the combinatorial explosion of the search space that would otherwise result from allowing arbitrary sequences of actions (infeasible solutions) before evaluation.

Computing the optimal multi-step schedule leads to faster solutions because it avoids the expense of computing optimal single-step solutions and then obtaining the overall multi-step optimal solution. With the use of heuristics, it is easy to ensure that multi-hour scheduling version will always produce a feasible schedule which is as good or better than a single-step algorithm.

The approach presented here can be very extended to include other objectives and constraints. Since, at each iteration, tournament is performed randomly on only one objective, the total time for the multi-objective problem is essentially the same as that for a single-objective. Another prominent feature of the proposed approach is that the execution time increases only linearly as the system size increases. The computation time can be considerably reduced by having a parallel implementation of the algorithm.

VII. CONCLUSION

The determination of optimum generating schedules for systems with multiple constraints and conflicting objectives is still a difficult task, despite many publications in this field. Traditional optimization techniques require well-defined performance indices for evaluating alternative solutions in the presence of mutually conflicting objectives. The heuristics-guided evolutionary approach presented in this paper overcomes this problem and provides the decision maker a whole range of alternatives along the Pareto-optimal frontier. It generates a large number of feasible solutions each with a certain trade-off between the objectives, emission and economy. This approach is particularly attractive due to its simplicity and intuitive appeal. Simulation results relevant to three test systems of different sizes have been presented in the paper. This approach has been compared with two genetic algorithm-based approaches. The superior performance of the proposed approach stems from its ability to make use of heuristics which guarantees that feasible solutions will always be generated. This overcomes the limitations of purely genetic algorithm-based approaches where infeasible schedules are generated making the models too time-consuming for practical use.

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IX. REFERENCES

1. Snyder, H. Powell, and J. Rayburn, "Dynamic programming approach to unit commitment", *IEEE Transactions on Power Systems*, Vol. 2 (2), p 421-428, May 1987.
2. Zhuang and F. Galiana, "Towards a more rigorous and practical unit commitment by lagrangian relaxation", *IEEE Transactions on Power Systems*, Vol. 3 (2), p 763-773, May 1988.
3. K. P. Wong, Y. W. Wong, "Genetic and Genetic/Simulated Annealing Approaches to Economic Dispatch", *IEE Proceedings C- Generation, Transmission and Distribution*, Vol. 141 (5), p 507-513, September 1994.
4. Dasgupta and D. R. McGregor, "Thermal unit commitment using genetic algorithms", *IEE Proceedings C- Generation, Transmission and Distribution*, Vol. 141 (5), p 459-465, September 1994.
5. H. Hassoun and P. Watta, Optimization of the unit commitment problem by a coupled gradient network and by a genetic algorithm, Technical Report TR-103697, Department of Electrical and Computer Engineering, Wayne State University, Detroit, Michigan, 1994.
6. H. Talaq, Ferial and M. E. El-Hawary, "A summary of environmental economic dispatch algorithms", *IEEE Transactions on Power Systems*, Vol. 9 (3), p 1508-1516, August 1994.

7. Nanda, D. P. Kothari,, and K. S. Lingamurthy, "Economic-emission load dispatch through goal programming techniques", *IEEE Transactions on Energy Conversion*, Vol. 3 (1), p 26-32, March 1988.
8. D. Srinivasan, C. S. Chang, A. C. Liew, "Multi-objective Generation Scheduling using Fuzzy Optimal Search Technique", *IEE Proceedings C- Generation, Transmission and Distribution*, Vol. 141 (3), p. 233-242, May 1994.
9. Arnone, A. Loraschi, and A. Tettamanzi, "A genetic approach to portfolio selection", *Neural Network World, International Journal on Neural and Mass-Parallel Computing and Information Systems*, Vol. 3 (6), p 597-604, 1993.
10. Horn, N. Nafpliotis, and D. E. Goldberg, Multi-objective optimization using the niched pareto genetic algorithm , Technical Report 93005, Illinois Genetic Algorithms Laboratory, University of Illinois at Urbana-Champaign, Urbana, 1993.
11. D. Schaffer,, "Multiple objective optimization with vector evaluated genetic algorithms", In J. J. Grefenstette, editor*, Proceedings of the First International Conference on Genetic Algorithms*, Hillsdale, NJ, 1985. Lawrence Erlbaum Associates.
12. A. Tettamanzi, A distributed model for selection in evolutionary algorithms, Technical Report 110-94. Dip. do Science dell'Informazione - Universita` degli Studi di Milano, Milano, Italy, 1994.
13. E. Goldberg, Genetic algorithms in Search, Optimization & Machine Learning, Addison-Wesley, Reading, MA, 1989.
14. Michalewicz, Genetic Algorithms + Data Structures = Evolution Programs, Springer-Verlag, Berlin, 1992.
15. E. Steuer, Multiple Criteria Optimization: Theory, Computation and Application, John Wiley & Sons, New York, 1986.
16. J. Wood and B. F. Woolenberg, Power Generation, Operation and Control, John Wiley & Sons, New York, 1984.
17. Srinivasan, A. C. Liew, and C. S. Chang, "Integrated security constrained generation scheduling in an interconnected system using AI approach*", International Journal of Engineering Intelligent Systems*, Vol. 1 (2), p 119-124, September 1993.
18. Syswerda, "Uniform crossover in genetic algorithms", in J. D. Schaffer, editor, *Proceedings of the Third International Conference on Genetic Algorithms*, San Mateo, CA, 1989, Morgan Kaufmann.