Dynamic Programming Based Metaheuristic for the Unit Commitment Problem

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1   Introduction

Unit Commitment Problem (UCP) is a strategic optimization problem in power system operation. Its objective is to schedule the generating units online or offline over a scheduling horizon such that the power production cost is minimized with the load demand fully met and the operation constraints satisfied. A fully description of the version of the UCP studied can be find in [1].

Dynamic programming (DP), an algorithm based on the search of the best path on a graph of states can be used to solve UCP. But in this case, the size of the graph grows quickly with the number of units. So in practice it is not possible to use it directly. Nevertheless, some adaptations of dynamic programming have been proposed for this kind of problems [2–4], but the guaranty of optimality is lost and the computation time remains substantial and further increases exponentially with the number of units. So, in practice, DP is not applicable to instances of large size.

In this paper an approach to solve the UCP called DYNAMOP for DYNAmic programming using Metaheuristic for Optimizations Problems is proposed. The main idea of this method is to use a genetic algorithm (GA) to run through the graph of DP. In the proposed GA a solution is modeled as a path of the graph of states of DP and so each gene will then be a state traversed by the path.

In the following section, DYNAMOP is introduced and its specificities are explained. Then results with comparison with the best results find on literature are proposed. And finally a conclusion about the potential of this method and perspectives are given.

2   DYNAMOP

The main idea of DYNAMOP [5] is to use a GA to find the shortest path in the graph of states of DP. Each phenotype represents a path in the graph of states from the initial state to one terminal state. In the case of the UCP a state is characterized by a time period and for each unit if it is turn on or off and for how long time. Finally an individual is a valid sequence of states. To be valid a sequence must be such that it is possible to pass from a state to the next one in respecting the time constraints (there is an edge, in the graph of states , between two consecutive states). Then DYNAMOP remains to a classical GA except that the evolutionary operators have to be adapted.

The mutation is to introduce a random change that will modify a minimal portion of the path. Here, as the fitness is the sum of the values of edges, the importance of change in the phenotypic level will be directly proportional to the number of edges changed in the genotypic level. So the mutation is designed in order to have the best possible locality property.

The crossover is to recombined two paths in using transition paths. After having selected a portion of path in one parent the idea is to attach this portion to the path of the other parent in using the minimum number of intermediate states (composing the transition paths). The advantage is that the fitness of the obtained offspring is the sum of the values of the portion of paths from the both parents plus the values of the transition paths. Then as the transition paths are constructed to be as small as possible, this leads to good heritability properties in phenotypic level. Indeed a crossover between two good individuals will most likely produce a good offspring and conversely a crossover between two bad individuals will lead to a bad offspring.

Actually these are great advantages of this choice of representation. Indeed with a classical representation were an individual is a sequence of decisions it will be very difficult to have good locality and heritability property because there is any separability of the fitness function in regard to the gene. But with the following representation the fitness function is the sum of the values of edges and so is almost separable in regard to the genes. An other advantage of this separability is that after applying an evolutionary operator only the values of the edges newly introduced have to be computed which leads in savings in computation time.

An other important advantage of this representation is that it allows to easily construct hybridization with DP. Here the hybridization is used as a boosting mutation whose purpose is to improve the current solution. The idea of this mutation is to construct a corridor around th considered path and to replace the path by the best path find in this coridor thanks to DP. This is exactly a step of Discrete Differential Dynamic Programming methodology [6]. Here a corridor is constructed in fixing the scheduling for some units.

3   Results and conclusion

The performance of the proposed DYNAMOP method is tested on the system with the number of units from 10 to 100 taken in literature. Table 1 summarizes the study results on the test systems in the last section above obtained by the proposed DYNAMOP method and other methods including [1, 7–9].

Table 1. Results and comparison with litterature

Number of units	DYNAMOP		Best known of litterature		GAP
	Best	time (s)	Best	time (s)	$\frac{Best\ known - DYNAMOP}{Best\ known}$
10	**563 938**	18	**563 938**	19	0%
20	1 123 297	50	**1 123 003**	19	0.026%
40	2 242 596	50	**2 242 167**	42	0.019%
60	**3 360 320**	100	3 361 980	328	-0.05%
80	**4 480 630**	130	4 481 863	113	-0.027 %
100	**5 599 150**	170	5 602 039	162	-0.05 %

Results obtained by DYNAMOP on instances with many units outperformed the results of literature. In the case were the best result of literature is better than the one obtained by DYNAMOP, DYNAMOP is very near to this best. Therefore we can say that the effectiveness and validity of DYNAMOP has been demonstrated through this application. On top that DYNAMOP has the advantage to be adaptable to any problem which holds Bellman's property and the proposed idea of representation can be reused to construct hybridization with an other metaheuristic.

To conclude with our perspectives of work, extend DYNAMOP to stochastic and multi-objective problems could be an interesting line of research.

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