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GENETIC ALGORITHM + LINEAR PROGRAMMING TO SOLVE A LOT-SIZING AND SCHEDULING PROBLEM

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Abstract

The aim of this work is to develop algorithmic solutions where we present results and analysis arising from the application of hybrid EA-based techniques and pure Mixed Integer Programming approaches to the lot-sizing and scheduling problem, model by [2].

The production system to be investigated has multiple products, parallel non-identical machines with sequence-dependent setup times at a single-stage. This lot-sizing and scheduling problem aims to minimize the total inventory and backlog costs by determining the quantities and sequence of the lots to be produced on each machine.

In order to obtain better solutions than the existing ones, we developed a hybrid approach by combining metaheuristic and mathematical programming methods. The combination of these methods is justified since exact methods for this kind of problem (i.e., NP-hard by [2]) can solve only small problem instances.

Problem solutions are represented as product subsets (ordered or unordered) for each machine m at each period t. The optimal lot sizes are then determined applying a linear programme.

Genetic algorithm searches either over ordered or over unordered subsets (the latter are implicitly ordered using a fast Asymmetric Traveling Salesman Problem [6], type heuristic) to try to identify an optimal solution. The GA is generational with the addiction of Elitism to help keep the best individual in each generation. We use as a selection mechanism the Binary Tournament Selection [1].

For the two basic GA operators, i.e. crossover and mutation, we chose the one-point crossover algorithm [3] considering the crossover point at the level of machines. For the mutation we implemented four different operators such as Replacement, Insertion, Deletion and Swap products in a randomly chosen subset.

After tuning some of the GA parameters we chose, based in the literature review, the following set: population size of 50 individuals, probability to reproduction of 90% and individual mutation rate of 0.05.

This paper closely follows the work done in [8] where now we are comparing the two GA hybrid approaches more broadly. The experimental tests are presented comparing the solution and time results for each GA encoding with a MIP from [2], using Cplex 7.5 [5], as mathematical programming solver, and also with other metaheuristic approaches, such as Simulating Annealing and Threshold Accepting by [7].

The instances tested represent different situations commonly found in industries environments, such loose capacity and also slightly tight capacity, by increasing the capacity along with the time-periods. The instances with increasing constant capacity were adapted from [4]. A benchmark of small theoretical instances are also provided to show the robustness of the hybrid GA approach.

Among of our observations we could say that the operators are independent of the lot-size and sequence features of this particular problem. They are general enough to be adapted for related optimization problem such as Knapsack Problems.

The combination of GA operators with the ordered encode solution and in a loose capacity environment, i.e. crossover and mutation, found the optimal solution for the small instances as well as traditional MIP. If we take into consideration the generation number when GA found it we could say, those solutions were found even faster than the MIP formulation, however by the nature of the GA we do need to run the algorithm for maximum number of generation of 100, as its stop criteria. For the large instance, Cplex was not even able to identify an initial solution for the MIP in the time taken by the GA.

Analyzing the results in [8] we are presenting now not only a single mutation operator in each run, but multiple mutation operators running at the same iteration, according a random choice of Insertion and Deletion operators, and secondly by using a smarter procedure such as choosing the operator according to the utilization of capacity on each machine-period pair.

Because of the inability of the algorithm to build a feasible first generation when the instance tested were bigger, i.e. $P=\{50, 100\}$, $M=\{10\}$ and $T=\{5\}$, we are using repair mechanisms on the infeasible individuals at this stage in order to test the scalability of the GA proposed.

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