An Hybridization of a Genetic algorithm with a Tabu Search for the Vehicle Routing Problem with Time Windows

Meriem Akli and Méziane Aïder

USTHB, Fac. Mathematics, LaROMaD, BP 32 El Alia, 16111 Algiers, Algeria
aklimeriem15@gmail.com, m-aider@usthb.dz,

1 Introduction

The genetic algorithm [4] is one of the most used approaches to solve NP-Hard problems [1]. Solving a variant of the VRP−TW [3] by just a genetic algorithm is constrained by an unbalance between the two components that are the research intensification and the diversification. Therefore, the idea of injecting a tabu search [4] procedure to balance between these components is very appropriate. The VRP−TW [1] variante we study is characterized by rigid time constraints. Indeed, the vehicle V_k serves a customer C_i only if it arrives in an instant $T_i^k \in [e_i, l_i]$.

2 Genetic-Tabu approach

The Genetic-Tabu (GT) is an hybridization [2] between a genetic algorithm with a tabu search. The hybridization process consists to inject a tabu search in several stages of a genetic algorithm. It contains two phases.

Initialization phase

In this phase we create an initial population[4] of solutions. The principle consists to consider a vehicle V_k and to draw a random customer C_i from the set $ECRS$ of the remaining customers to serve. If his request d_i is less than the remaining capacity CR_k of the vehicle, then the customer C_i will be served by the vehicle V_k, else we randomly draw another customer from $ECRS$, until $CR_k \leq \min_{i \in ECRS}\{d_i\}$. In this case, a new vehicle is mobilized. This process of vehicle capacity saturation is repeated until all customers are served.

Improvement phase

This is a crucial step in GT approach. It consists of three procedures:

Selection From an initial population of solutions P of size m, we construct the set PC of all the possible pairs of solutions in P. Then, take a random sample E from PC as candidates pairs of solutions to crossing.

Crossing The particularity of the chosen crossing is that it takes into account the distance between the last customer inserted in the child solution and the customers in the parents solutions. Given the remaining capacity of the outstanding vehicle saturation in the child solution and the time window, insert the customer in the parents solutions closest to the last customer inserted in the child solution.

Evaluation and Re-insertion This step has a direct impact on the intensification and the diversification of the GT approach. Indeed, if the child solution is better than both the parents solutions then it is re-inserted instead the worst parents solutions in E only for ensuring the intensification. Eliminating the worst parents solutions in E ensures the diversification. Now, if the child solution is worse than the two parents solutions, no change is made to the starting populations P and E.

3 Numerical results analysis

The GT algorithm is implemented in C on Linux. The tests are performed on six (06) categories of instances of Solomon benchmarks, loaded on $//w.cba.neu.edu/msolomon/problems.htm$. These instances are grouped into three (03) categories: problems with the positions of the customers randomly generated $POSR$, problems that position of customers is divided into clusters $PosC$ and problems in which the position of the customers is both distributed in clusters and randomly generated $PosRC$. The size of these instances is ($n = 100$).
The algorithm GT provides solutions to all these instances, with:

1. A decreasing of the total traveled length ($1143, 20 \longrightarrow 1106, 56$) but with an increasing number of mobilized vehicles ($8 \longrightarrow 9$) for the category $POSR$.
2. A decreasing of the total traveled length ($3033, 68 \longrightarrow 1218, 68$) and a decreasing number of mobilized vehicles ($9 \longrightarrow 8$) for the category $PosRC$.
3. For the category $PosC$, the previously obtained solutions have not been improved. This can be explained by the principle of the chosen crossing process based on the nearest neighbor so the distribution of the customers on a cluster can be upsetting this principle.

4 Evaluation of GT Approach

The stopping criteria related to the size of the initial population and the selected sample and the crossing principle are the main influent parameters of the GT approach.
The size of the initial population is fixed in advance. Its increase improves the quality of the solutions, but the execution time is large, since the numerical results show that 80% of the execution time are dedicated to the creation phase of the initial population and only 20% to improvement. The same phenomenon was observed for the sample size.
Taking the quality of the solution as a stopping criterion may generate a population of very large or very small size (extreme situations) which lead to an unbalance between the intensification and the diversification.
The Efficiency of the selected crossing process appears in the improvement of the initial population of more than 60%. Indeed, for the category $PosRC$, the value of the best solution is improved from the the value of the best solution in the initial population from $3033, 68$ at $1218, 68$.

5 Conclusion

The experimental results of the GT approach show that in its first phase it provides a good diversification of the solutions but without guaranteeing the quality. Indeed, compared with the results obtained on the Solomon benchmark one can see that the solutions are different from those of the benchmarks. With the improvement phase, we obtain solutions of quality more similar to those of the Solomon benchmark and even better in the case of problems with parameters generated randomly. Diversification is achieved by taking the sample.

References

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