A Hybrid Particle Swarm Optimization for Solving Vehicle Routing Problem with Time Windows

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ABSTRACT

This paper presents a hybrid Particle Swarm Optimization (PSO) for solving Vehicle Routing Problem with Time Windows (VRPTW). Three versions of the algorithm were implemented. The first version is a traditional PSO. In this case, the initialization is random and the best insertion for each customer on the route is evaluated. The second version is a combination of Greedy Randomized Adaptive Search Procedure (GRASP) and Push-Forward Insertion Heuristic (PFIH) with PSO. The last version, in addition to the previous characteristics, features a mutation operator after updating speed and position of each particle. For computational experiments, the 56 Solomon's instances are used and the results obtained in each version are compared with the best known results from literature. A statistical analysis indicates that the third version has a better performance than the other versions.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods*

General Terms

Algorithms, Experimentation, Verification

Keywords

Swarm Intelligence; Particle Swarm Optimization; Hybridization; Metaheuristics; Combinatorial Optimization

1. INTRODUCTION

This paper presents a hybrid Particle Swarm Optimization (PSO) for solving Vehicle Routing Problem with Time Windows (VRPTW). The hybridization of the evolutionary algorithm consists of a combination of the Greedy Randomized Adaptive Search Procedure (GRASP) and Push-Forward Insertion Heuristic (PFIH) with PSO and a mutation operator to the PSO. The goal is to verify if the inclusion of metaheuristics and other techniques improves PSO performance.

The use of metaheuristics for solving it is justified since VRPTW belongs to the NP-Hard class problems [6]. [1] proposed a PSO with discrete variables to solve the Capacitated Vehicle Routing Problem. [4] utilized a Multi-Objective Genetic Algorithm to solve the VRPTW. A mutation operator, named Constrained Route Reversal Mutation (CRRM), is proposed in order to escape of local optima. The CRRM is based in a simple process of route inversion of an stretch randomly determined. [2] combined a Chaotic Optimization algorithm to the PSO, in order to restart the swarm's particles, a Gaussian strategy to avoid local optima and an insertion algorithm to build VRPTW routes in the proposed decoding process.

2. PROPOSED ALGORITHM

The first version is a traditional PSO, named TPSO. The main modification is the random initialization of the swarm particle and the customer to be inserted is chosen in a random manner. However, it will be inserted in the best-found location at the moment and in the routes already created by the encoding process. The swarm is composed by 100 particles in total. The stopping criteria is the union of the obtained solution quality and number of iterations without improvement of the result.

The second version of the proposed algorithm is a combination of GRASP and PFIH with the PSO (GPPSO). The construction phase of GRASP uses PFIH as its greedy characteristic. The second phase of GRASP performs a local search to refine the generated solution in the previous phase.

The last version is a hybrid PSO. Additionally to the GPPSO characteristics, the mutation operator CRRM proposed by [4] was inserted after the updating of the particles swarm. The adaptation made on the CRRM is found in the maximum number of customers contained in the reversed stretch. It is inversely proportional to the particle quality: the better the solution is, the lower is the number of inverted customers.

3. COMPUTATIONAL RESULTS

The computational experiments were run on a Intel Core i7 2.40Ghz with a 8GB RAM memory and Windows 8.1 operational system. The 56 instances from [5] with 100 customers for the VRPTW were tested. The algorithm was executed 40 times for each one of the implemented versions. Table 1 shows the average number of vehicles and average

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Table 1: Average by Class and Total Results

Class	Best Know	TPSO	GPPSO	HPSO
C1	10|828.38	10.22|829.30	10|828.38	10|828.38
C2	3|589.86	3.38|602.05	3|589.86	3|589.86
R1	11.92|1209.89	12.75|1239.22	12.25|1214.21	11.92|1209.89
R2	2.73|951.02	4.46|1003.20	3.64|964.25	3.1|958.85
RC1	11.5|1384.16	13.38|1493.46	12.75|1448.64	11.5|1384.16
RC2	3.25|1160.75	4.75|1157.5	4.5|1145.92	3.75|1157.35
Total	405|56352.70	466|59393.53	439|58109.3	413|56418.54

total traveled distance by each class of Solomon's instances and each implemented version of the algorithm. The best known results in the literature were taken from `http://www.sintef.no/Projectweb/TOP/VRPTW/Solomon-benchmark/`.

4. STATISTICAL ANALYSIS

To evaluate the hybridization effect of the GPPSO, the quality of the solution for the initial particle swarm was verified. Figure 1 shows the boxplot generated based on the fitness function of each particle in the initial swarm after 40 executions of the versions TPSO and GPPSO.

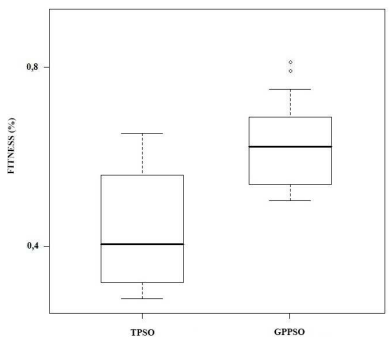

Figure 1: Boxplot for initial particle swarm solutions.

From Figure 1, apparently, particles from the GPSO initial swarm are better than the TPSO particles. However, because these version' data overlapped, nothing can be concluded through the visual analysis of the boxplot. According to [3], the statistical method ANOVA allows us to estimate averages of populations. Considering the null hypothesis (H_0) that significant differences between the initial particle swarm TPSO and GPPSO are inexistent, the alternative hypothesis (H_1) indicating that exist difference between the versions and $\alpha = 0.05$, an ANOVA test was created resulting in a $p - value$ equals 0.006. Based on this value, it was possible to refute H_0 with 95% confidence, concluding that statistically significant differences do exist between the TPSO and GPPSO. In other words, with a 95% of statistic significance, the GPPSO initial particle swarm is better that the HPSO initial particle swarm.

Figure 2 shows a second boxplot generated from the obtained results with each version of the implemented algorithms after 40 executions. Unlike the previous boxplot, this corresponds to an obtained solution at the end of execution of each version, not with the initial particle swarm.

Another ANOVA test was created resulting in a $p - value$ equals 0.017, concluding that statistically significant differences do exist between the three versions. In order to evaluate the magnitude of the difference, three Tukey's Tests were performed between each version. In all tests $\alpha = 0.05$ was fixed. The first test generated a confidence interval with a lower limit to 0.2274 and a upper limit to 0.9729. The second test presented confidence interval limits of 0.8234 and 1.5719. The last test presented confidence interval with a lower limit to 0.4277 and a upper limit to 5.6714. Since the 0 value does not belong to the interval of all tests, it is concluded that differences between this three versions' means are existent.

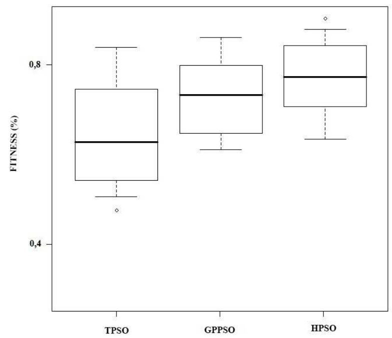

Figure 2: Boxplot for final particle swarm solutions.

5. CONCLUSIONS

The statistical analysis of the experiments shows that the adopted hybridity produced positive effects and that the robustness of the proposed algorithm was improved in each version. Furthermore, it was possible to verify that, with a statistical significance of 95%, the GPPSO initial particle swarm solution is better than the TPSO. In the final result of the HPSO there was a difference of 8 vehicles from best known in the literature. With 95% statistical significance, it was verified that the last version developed is in fact the best of all three versions of the implemented hybrid population-based algorithm.

6. ACKNOWLEDGMENTS

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