A New Diversification Measurement Technique in Metaheuristics for Vehicle Routing Problems

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Abstract

This article presents a technique to measure the diversification effect of local search moves in metaheuristic algorithms for solving capacitated vehicle routing problems. The diversification values calculated through this technique can be used to modify the algorithms, pick the best neighborhoods in each move and improve the searching process to find the optimal solution. This technique may be implemented to a wide variety of metaheuristics. It is shown that metaheuristic algorithms for vehicle routing problems may be examined efficiently and improved with this technique. Moreover, we examine the solutions for different instances produced by this technique on simulated annealing algorithm and we interpret the relations between the optimal solution and the diversification scores.

Keywords
Vehicle routing, metaheuristics, neighborhood search, simulated annealing, diversification

1. Introduction

The vehicle routing problem (VRP) is a combinatorial optimization problem, searching to find the optimum routes for delivering the products to customers. Capacitated VRP (CVRP) is a type of VRP problem where vehicles are assumed to have a limited capacity and properties of vehicles are assumed to be the same. There exists a central and single depot, the deliveries and demands may not be split, deterministic and known in advance. As the properties of the problem change, problem type of VRP may change accordingly.

The VRP problem is an important combinatorial optimization problem due to the fact that there are many real life applications. It has been studied via many methods and many attempts have been made to obtain optimal or convergent solutions. Even though many solution methods have been developed for these problems, most of them is observed to require a long time to provide a good solution. However, in real life, managers generally require a good solution in a very short time, thus it becomes important to develop models that provide convergent solutions in a short time period. Metaheuristic algorithms have been proposed in literature that may achieve good results in large quantities in a short time due to these needs.

In recent years many new metaheuristic algorithms are developed. Some of them are single solution based algorithms which are searching form the reference of one single solution. Single solution based algorithms are easy to implement and they are efficient algorithms requiring less memory. Simulated annealing, tabu search, variable neighborhood search methods are the examples of these algorithms. Also, there is population based algorithms which make multiple point searches within a single iteration. Genetic algorithms, partical swarm optimization, ant colony algorithms are some of these algorithms. The hybrid of those algorithms are also generated according to needs as well.

Some metaheuristics are using neighborhood search algorithms as hybridized and the challenges in this type of studies are to stuck in a local minimum or not having a good result in a reasonable amount of computation time. Selection of the neighborhood search algorithm for a metaheuristic has great importance in this area. Especially in the existence of a wide variety of choices for neighborhoods, a good criterion is needed to decide which neighborhood to choose in the next move. In order to obtain a convergent optimal result, there are some requirements that a metaheuristic algorithm has to have, and one of them is diversity. If an algorithm has a certain measure of diversification (not too much or less) it may deal with both two challenges: stucking to local minimum and not concluding in a certain time. However, there does not exist a common technique in literature to measure the diversification amount in a metaheuristic algorithm. Thus, we propose a method to measure the diversification of an algorithm for making a decision about the next choice of neighborhood.

In this study we describe a technique for measuring diversity of a neighborhood search algorithm and we illustrate this technique on CVRP (Capacitated Vehicle Routing Problem) via simulated annealing algorithm. This technique also can be applied on different neighborhood search algorithm (NS) or metaheuristic algorithms. The rest of the paper is organized as follows. In section 2 literature, review is described. In section 3 technique is clarified in detail. In section 4 computational results and application is stated. In section5 conclusions and interpretations are presented.

2. Literature Review

The importance of neighborhood search has led to a number of studies in the OR literature. Several methods are generated for the purpose of obtaining good global results or to get good results quickly. Christofides and S. Eilon(1969) use r-opt tour method for neighborhood search technique and find 3-opt has good results for vehicle dispatching problems. Russell (1977) use k- opt improvement heuristic in order to obtain global tour improvement with tour construction process for VRPTW. Or(1976) introduces Or-opt operator as neighborhood selection method for traveling salesman problems. Fisher and Jaikumar (1981) introduce cluster first, route second algorithm for VRP problems. Taillard (1997) develops cross exchange neighborhood search method for VRP soft time window problems. Osman (1993) uses 2-opt and insert/delete procedures together in order to find a fast way to approximate cost exchanges for VRP. Bräysy and Gendreau (2005) use first accept best accept neighborhood search method. Kedad-Sidhoum and Sourd (2010) develop composite neighborhood search and use in iterated local search algorithm for job scheduling problem. They focus on reducing the timing by large scaling for neighborhood search. Lei and Wang (2011) develop an effective neighborhood search algorithm for batch processing machine scheduling problem. They emphasize the importance of effective neighborhood selection in order to reach new solutions. Wang et. al. (2012) enhance diversity with neighborhood search algorithm. Studies above analyze the NS techniques and use them according to necessities or they generate different methods for different problems or within different algorithms.

Mladenovic and Hansen (1997) introduce the variable neighborhood search (VNS) algorithm, using the idea of changing the neighborhood search inthe algorithm and exploring increasingly distant neighborhoods. Shaw(1997) generate a large neighborhood search (LNS) algorithm, starting with small neighborhoods and gradually increasing the size of the neighborhoods. Main purpose of the study is to reduce the computation time. Ropke and Pisinger (2006) advance the LNS algorithm by controlling and dynamically selecting neighborhoods according to the performances of their history within the adaptive large neighborhood search (ALNS) algorithm. These three studies claim that large neighborhood search methods can find good results by differentiating the neighborhood search (NS) methods within the algorithm.

In addition, some studies focus on comparing neighborhood selection methods. Glass and Potts (1996) compare neighborhood search algorithms (neighborhood structures) according to the relative deviation from best knowns, as effectiveness of the algorithms for job scheduling problems. Ahujaet al. (2002) declare the importance of large-scale neighborhood search methods and compare very large-scale neighborhood search algorithms. Blum and Roli (2003), compare metaheuristics considering their impact of diversification and intensification. They underline that diversification and intensification effects are critical for a local search algorithm.

According to the papers touched on, selection of neighborhood search method is crucial for metaheuristics. Glass and Potts (1996), Ahujaet al.(2002), Blum and Roli (2003) compare NS methods by acceptance amounts according to the technique they use. The aim of this study is to generate a neighborhood selection technique that makes decisions faster and more accurately. We focus on the idea of searching a large neighborhood to increase the chance of finding better solutions (Pisinger&Ropke 2010). So, we claim that the diversification value can be a good measurement unit for selecting large neighborhoods, and thus we use diversification as a criteria of neighborhood selection.

3. Problem Description

The CVRP includes searching for optimal routes which are the departure sequence of the customers The depot is predetermined as starting and ending points. The demands from customers have been announced in advance and all customers has to be visited exactly by one vehicle for once. The vehicles have the same capacity and carry one kind of product. Also the vehicle has to fulfill the total demand in one visit. The objective is to minimize the total distance and/or number of vehicles used. The representation of routes may vary in different structures. Most common and most efficient way is to build a permutation of cities that have demands. The permutation of cities has to start with city where the depot is and also ends at the depot as well. A route with seven cities is shown in Figure 1 as a permutation representation for one vehicle. For each vehicle a route is built as a permutation of the remaining cities.

1	7	2	4	6	3	1

Figure 1. An instance of permutation representation for a route

4. Proposed Technique

Recently, the significance of diversification has been mentioned a lot in literature and due to this significance, different local search methods or metaheuristics have been generated to increase diversification effect of algorithms. In the process of developing a new metaheuristic, measuring the diversification performance of the algorithm could be required to understand the effectiveness of the algorithm. According to this idea, we generate a new technique that determines the diversity obtained by the search moves in an algorithm.

When measuring the performance of any process, the relation between inputs and outputs as indicators of productivity are evaluated. Inspired form this idea we evaluate diversification effect according to the difference between current solution as an input and accepted neighborhood solution as an output of the algorithm.

By this way, total algorithm can be evaluated according to diversity step by step. Through this technique we measure how much the algorithm has progressed in each iteration in the name of diversification. This technique can be a comparison technique for metaheuristic algorithms that gives information about the diversification related to itself before the algorithm is finished.

For CVRP problems cost is a goal for optimizing the tours according to the circumstances on hand. Alternation of cities in tours affect the cost. For this reason, alternations between the new tour and the accepted neighborhood tour are determined and scored for diversification. Two types of alternation is examined

- Index Alternation
- Edge Alternation

According to index alternation, diversification value is determined according to the index values of the current and neighborhood solutions. If accepted neighborhood solution has a value change, it takes one point for index alternation. For all sub tours for each neighborhood, indexes are examined in this way according to the previous solution index. The sum of scores for a tour is obtained as the diversity score for index alternation. An example is shown in Figure 2.

0	0	0	1	1	1
1	7	11	6	1	
1	7	11	8	10	1

Figure 2.Index alternation

For edge alternation, the technique examines the links in each tour. If neighborhood solution has an edge that initial solution has not, than 1 point is given. So each tour have a score obtained by the sum of diversity scores of edges. Sum of all tour points in a whole solution is used as the diversity score. For example, let first rows in Figure 3 denote the initial solutions and second rows denote the accepted neighborhood solution. According to Figure 3, 2 points is obtained as the diversity score of this neighborhood.

1	7	11	6	1
1	7	11	6	1

1	5	12	10	1
1	5	12	13	1

1	2	9	8	3	1
1	2	9	8	3	1

1	4	13	1
1	4	10	1

Figure 3. Edge alternation

For each iteration of the algorithm, diversity score is calculated and the diversification performance of the algorithm is known before the algorithm is finished. The choice of the next move can be adapted according to the diversity scores of different moves, leading to a better search space in the algorithm. We expect that using the diversification scores in the neighborhood search process will lead to better results in a shorter time.

5. Computational Results

The proposed algorithm was implemented using Python on an Intel Core i52.60GHz with 8GB of RAM and tested on various instances from http://neo.lcc.uma.es/vrp/. The set of benchmarks that we have attempted are the instances from Augerat’s benchmark. Each benchmark was solved by simulated annealing algorithm with 3 different NS methods.

For simulated annealing the cooling schedule includes the set of parameters controlling initial temperature, iteration multiplier, the number of iterations for each temperature, temperature reduction multiplier and stopping temperature. After initial test runs, initial temperature was set to 5000, iteration multiplier was set to 1.05 and number of iterations for each temperature was taken 250, while temperature reduction multiplier was 0.99. Algorithm stops when temperature is below 0.001.

From the experiments, it is obtained that diversification effect for simulated annealing algorithm is generally better for 2-opt NS. In the development phase of the algorithm the use of two different neighborhood structures can be considered to increase the diversification effect. However, this study shows that different neighborhood utilizations may not exceed the diversification effect of the single neighborhood method. For this reason, it would be useful to measure this effect and make decisions according to this measurement. It is also seen in Table 1 that results of objective value has the highest value with the method of the highest diversification score.

Table 1. Results for instances

Benchmarks	Diversification Score	NS method	Cost (Best Obtained)	Cost (Best Known Optimal Obtained)	Difference From Optimal
A-n32-k5	844920	Swap	879.47	784	1.21%
	1091593	2opt+Swap	862.97		
	1456996	2-Opt	**793.47**		
A-n33-k5	881015	Swap	723.63	661	1.94%
	1168023	2opt+Swap	758.13		
	1555120	2-Opt	**673.84**		
A-n33-k6	819877	Swap	807.88	742	2.85%
	1102066	2opt+Swap	800.22		
	1254225	2-Opt	**763.13**		
A-n36-k5	818170	Swap	875.85	799	5.92%
	1212168	2opt+Swap	919.29		
	1500380	2-Opt	**846.28**		
A-n37-k5	903160	Swap	775.00	669	0.52%
	1212526	2opt+Swap	833.14		
	1774450	2-Opt	**672.46**		
A-n37-k6	867694	Swap	1071.82	949	9.47%
	1048420	2opt+Swap	1045.07		
	1371873	2-Opt	**1038.85**		

The experiment results showing the diversification scores and the best solutions are given in Table 1. Different NS methods were tested on different benchmarks. It is observed that the NS method having closest value to optimal has a higher diversification score. In addition, it is observed that as the diversification score increases, the convergence also increases. In order to show the progression of the diversification scores of NS methods throughout the runtime of the algorithm clearly, we present the graph for the instance A-n37-k5 in Figure 4. The diversification scores are measured while the algorithm is running and the progression of the scores are observed as in Figure 4. Using these results, algorithms can be modified or evaluated during the running period. In addition, we state that the diversification score can be an indicator of better moves and can be used in choosing the best NS method and also be used to modify the algorithm, for example in parameter setting.

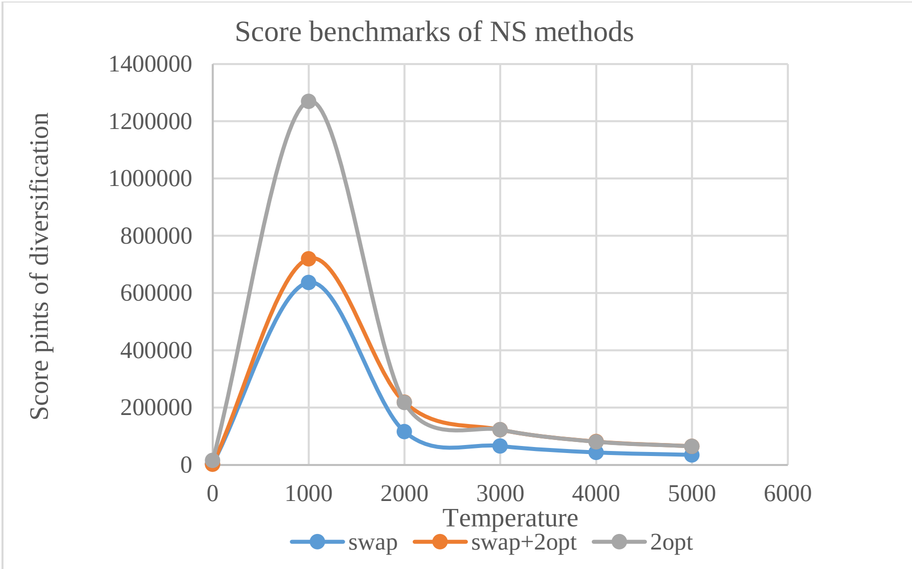

Figure 4. Diversification scores for NS methods

6. Conclusion

We have presented a new technique that measures diversification effect of metaheuristic algorithms for capacitated vehicle routing problems. The problem is solved using simulated annealing algorithm with different NS moves. It is obtained that diversification measure is an important factor for the success of metaheuristic algorithms and NS methods. In addition, this technique may help to make decisions for NS selection or to evaluate metaheuristic algorithms.

We propose a new technique that is able to calculate diversification scores and analyze metaheuristic algorithms with hybrid mechanisms according to these results. These scores show us how diversified the algorithm is. This ability of the algorithm can be used as a criteria to decide whether the diversification in the algorithm is appropriate or not, and whether the algorithm needs to be improved. Our technique may be useful in measuring the diversification in the algorithms and can be a very important indicator for metaheuristics. It can be used to improve the success of the metaheuristics by helping to choose the best neighborhood structure in the next moves. It can also help in decision making about the combination of two or more neighborhood structures to be used as hybrid approaches.

The relationship between the diversity score and the objective function value is tested for different NSs. The objective function in different problems with different algorithms has been observed from the experiments and the value of the objective function is seen to improve as the diversity score increases. The algorithms with high diversification scores are observed to be more successful and achieve better results.

It is also as seen from the results that using two different NS methods in order to increase the diversification effect, may not always increase the diversification effect more than using a single NS method. For this reason, diversification scores need to be measured for decision making about which NS mechanisms to use. We finally state that the measurement of diversification scores in algorithms can provide very useful results in improving the algorithms and we will focus on the usage of this technique for different combinatorial problems in the future.

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Biography

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