A dynamic approach for the vehicle routing problem with stochastic demands

Victor Pillac, Christelle Guéret, Andrés Medaglia

A dynamic approach for the vehicle routing problem with stochastic demands

Victor Pillac[1,2], Christelle Guéret[1], Andrés L. Medaglia[2]

[1] Équipe Systèmes Logistiques et de Production, IRCCyN (UMR CNRS 6597)
École des Mines de Nantes, B.P.20722, F-44307 Nantes Cedex 3, France
{vpillac,gueret}@mines-nantes.fr

[2] Centro para la Optimización y Probabilidad Aplicada (COPA) & CEIBA, Ingeniería Industrial
Universidad de los Andes, Cra1 Este No.19A-10 Bogotá, Colombia
amedagli@uniandes.edu.co

Keywords : *dynamic vehicle routing, VRP with stochastic demands, multiple scenario approach.*

1 Introduction

The Vehicle Routing Problem with Stochastic Demands (VRPSD) is a variation of the classical Capacitated Vehicle Routing Problem (CVRP) in which the demand of each customer is modeled as a random variable and its realization is only known upon vehicle arrival to the customer site. Under this uncertain scenario, a possible outcome is that the demand of a customer ends up exceeding the remaining capacity of the vehicle, leading to a route failure. In this study we will focus on the single vehicle VRPSD in which the fleet is limited to one vehicle with finite capacity, that can execute various routes sequentially.

Traditional approaches for this problem involve a two-phase procedure [1, 3]. In the first phase, the problem is solved a-priori with the goal of finding a set of robust routes ; while in the second phase routes failures are handled by means of recourse actions, such as forcing the vehicle to go back to the depot and restore its capacity, to then visit the client again and serve the remaining demand.

Recently, new approaches were developped based on the dynamic re-optimization of the vehicle routes [6, 7, 5]. In this context the routing is no longer done a-priori but instead performed (and re-optimized) throughout the day : as soon as the vehicle becomes idle, a decision has to be taken regarding the next customer visit. The algorithms proposed by the aforementioned authors offer greater flexibility in comparison with two-stage approaches, allowing significant cost reductions. However, they assume discrete uniform demand distributions and have to be run every time a decision has to be taken, which can be time consuming for large instances.

The present work is based on an adaptation of an optimization framework developed initially for the vehicle routing problem with dynamic customers (i.e., customers appear while the vehicles are executing their routes).

2 Approach

In the Multiple Scenario Approach (MSA) [2] a pool of scenarios is continuously optimized and updated to capture the uncertainties. Even if internally each scenario in the pool contains a complete routing for the customers, the only information visible to the user is the next customer to visit. This study proposes an adaptation of this framework to the VRPSD, by maintaining a pool of scenarios containing possible realizations of the customer demands. Scenarios are optimized with and Adaptive Variable Neighborhood Search and the next client to visit is selected with a Consensus algorithm.

3 Preliminary Results

Preliminary computational experiments show that our method is competitive against the algorithms proposed in [6, 5], even if the test instances are not favorable as the customer locations are randomly distributed and their demands follow a uniform discrete distribution causing high variability in scenarios and realizations.

	Instance set (size,capacity)					
Algorithm	**(30,137)**	**(30,87)**	**(40,183)**	**(40,116)**	**(60,274)**	**(60,175)**
Secomandi [6]	12.3%	11.8%	11.1%	12.9%	13.9%	19.6%
Novoa and Storer [5]	3.5%	**3.6%**	**3.0%**	**5.4%**	**2.8%**	10.7%
MSA	**0.9%**	4.1%	3.5%	6.3%	2.9%	**2.0%**

TAB. 1 – Comparison of average gaps relative to the perfect information solutions

Table 1 presents preliminary results for instances with 30, 40 and 60 customers from the Novoa benchmarks [4] with an experimental setting identical to the one presented in [5]. It can be noted that MSA dominates the algorithm proposed by Secomandi [6], while it outperforms the best performing algorithm reported in [5] for the set of 60 customers instances with a vehicle capacity of 175. MSA is run continuously, and the next customer to visit is selected in a fraction of second, while the other algorithms can take up to various minutes.

4 Conclusions and research perspectives

We have demonstrated the flexibility of the Multiple Scenario Approach by adapting it to the VRPSD. Preliminary experiments show encouraging results, both in terms of routing cost and decision time, while relaxing assumptions on customer demand distributions. Further work will focus on the generalization to the multiple vehicles case and other customer demand distributions.

References

[1] Jean-Francois Cordeau, Gilbert Laporte, Martin W.P. Savelsbergh, and Daniele Vigo. Vehicle routing. In Cynthia Barnhart and Gilbert Laporte, editors, *Transportation*, volume 14 of *Handbooks in Operations Research and Management Science*, chapter 6, pages 367 – 428. Elsevier, 2007.

[2] Pascal Van Hentenryck and Robert Bent. *Online stochastic combinatorial optimization.* MIT Press, 2006.

[3] Jorge E. Mendoza, Bruno Castanier, Christelle Guéret, Andrés L. Medaglia, and Nubia Velasco. A memetic algorithm for the multi-compartment vehicle routing problem with stochastic demands. *Computers & Operations Research*, 37(11) :1886–1898, November 2010.

[4] Clara M. Novoa. *Static and dynamic approaches for solving the vehicle routing problem with stochastic demands.* PhD thesis, Lehigh University, Pennsylvania, United States, 2005. AAT 3188502.

[5] Clara M. Novoa and Robert Storer. An approximate dynamic programming approach for the vehicle routing problem with stochastic demands. *European Journal of Operational Research*, 196(2) :509–515, 2009.

[6] Nicola Secomandi. A rollout policy for the vehicle routing problem with stochastic demands. *Operations Research*, 49(5) :796–802, 2001.

[7] Nicola Secomandi and Francois Margot. Reoptimization approaches for the vehicle-routing problem with stochastic demands. *Operations Research*, 57(1) :214–230, 2009.