A dynamic approach for the vehicle routing problem with stochastic demands

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Agenda

- The Vehicle Routing Problem with Stochastic Demands (VRPSD)
- The Multiple Scenario Approach (MSA)
- Computational results
- Conclusions and future work



The VRPSD

- Extension of the Vehicle Routing Problem
 - Set of customers
 - Fleet of vehicles
 - Design a set of routes minimizing distance
 - Stochastic Demands
 - Known distribution law
- Route failure
 - Demand realization exceeds remaining capacity
 - Split delivery



The VRPSD

- Some applications
 - Milk recollection
 - Garbage recollection
 - Heating oil delivery



Motivation

- Traditional approaches
 - Two-stage approach
 - Robust a-priori routing
 - Recourse actions in case of failure
 - Assumes vehicles cannot be rerouted
- Why a dynamic approach?
 - Increasing availability of low-cost positioning systems
 - Real-time communication with vehicles
 - Allows further optimization



State of the art

- Reoptimization/dynamic approach
 - Novoa & Storer (2009), Secomandi (2001), Secomandi & Margot (2009)
 - No a-priori routes
 - Optimization performed at each decision time
 - Discrete uniform demands
- Assumptions
 - Single vehicle
 - Failure
 - Split delivery
 - Replenishment trip



Multiple Scenario Approach (MSA)

- Optimization framework for online optimization
 - Van Hentenryck and Bent (2006)
- Runs throughout the day
- Scenario pool
 - Realizations of the random variables
- Decision process
 - Which client next?
 - Aggregate scenario knowledge
- Java implementation (jMSA)





MSA - Events

• Time line of events



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MSA - Algorithm











jMSA – Scenario pool

• Shrinking of executed route

• Sampling of the customer demands





jMSA - Decision

- Consensus
 - Select the customer that appears first with the highest frequency



- Others
 - Regret, detour regret ... dominated



jMSA – Route failures

- Occurs when the customer demand exceeds vehicle capacity
 - Split delivery
 - Reinsertion of following customers





jMSA - Optimization

- Adaptive Variable Neighborhood Search (AVNS)
 - Swap, 2-opt, Or-opt, string-exchange
 - Adaptive neighborhood selection
 - Based on performance
 - Selection wheel
- Performance
 - Fast (~200ms)
 - Average gap: 1.4%



GAP Distribution

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jMSA - Parallelization

- Parallelization of
 - Scenario generation
 - Scenario optimization
- Benefits
 - Increased reactivity
 - More optimization in the same time



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Computational experiments

- Instances from Novoa (2005)
 - 30, 40 and 60 customers
 - Randomly distributed in 1x1 square
 - Uniform discrete demand distribution
 - 2 vehicle capacities
- Simulation
 - MSA used as a *black-box*
 - 100 runs per instance
 - 3-5 min per run
 - 3000 runs in total (10 days)





Computational experiments

- Average value of information
 - Gap to perfect information (in %)

		(size,capacity)								
Algorithm		(30,137)	(30,87)	(40,183)	(40,116)	(60,274)	(60,175)	Average		
Secoman 2001	^{di} 1s_n2_r	12.25	11.82	11.15	12.87	13.88	19.63	12.25		
	1s_n2reopt_r	16.02	12.32	12.48	12.97	14.02	19.75	16.02		
Novoa & Storer 20	₀₀₉ 1s_stostat_r	4.67	5.06	3.66	5.27	3.52	12.35	4.67		
	2s_stostat_r	3.45	3.62	2.95	5.38	2.78	10.70	3.45		
	MSA	0.91	4.07	3.55	6.26	2.94	2.00	3.16		

- Faster decisions (ms vs min)
- Flexibility
 - Other distributions



Computational experiments

- Normal distribution
 - Based on Novoa (2005) instances
 - e.g.: Uint(11,15) → N(13,1)

		(size,capacity)										
Algorithm		(30,137)	(30,87)	(40,183)	(40,116)	(60,274)	(60,175)	Аvегаде				
MSA	Uniform	0.91	4.07	3.55	6.26	2.94	2.00	3.29				
MSA	Normal	0.66	3.61	3.39	6.21	2.23	1.92	3.01				



Computational experiments

• GAP distribution for size 60 instances





Conclusions

- New approach for the VRPSD
 - Dynamic
 - Increased reactivity
 - Generic
 - No assumption on demand distributions
 - Additional constraints
- Future work
 - Extend to multiple vehicles
 - Design specific decision process
 - Use stochastic modeling



References

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Questions & Answers

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Thank you for your attention

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