中国科学技术大学
University of Science and Technology of China

Hybrid PACO & Pheromone Initialization for VRPTWs

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  - vehicle capacity and time windows must not be violated

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  - f_1 often considered as more important, since using more vehicles costs more than driving a bit longer

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  - next vehicle is used, until all customers are satisfied

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  - we hybridize the algorithm to further improve the result quality

Existing ACO Methods

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Algorithm 1 vs. 2		-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0
ACS	IACO	0	40	16	0	52	4	0	40	16	1	51	4	0	44	12	0	54	2	0	124	44	1	157	10
ACS	MMAS	0	49	7	1	51	4	0	41	15	9	36	11	2	36	18	35	7	14	2	126	40	45	94	29
ACS	PACO-ABS	0	12	44	9	31	16	0	35	21	5	45	6	0	54	2	0	51	5	0	101	67	14	127	27
ACS	PACO-EBS	0	47	9	0	54	2	0	48	8	0	54	2	0	55	1	0	52	4	0	150	18	0	160	8
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MMAS	PACO-QBS	3	1	52	16	15	25	0	33	23	0	52	4	0	55	1	0	56	0	3	83	76	16	123	29
PACO-ABS	PACO-EBS	0	0	56	5	1	50	3	0	53	19	2	35	28	0	28	48	0	8	31	0	137	72	3	93
PACOABS	PACO-QBS	0	0	56	0	3	53	0	1	55	0	13	43	0	1	55	1	28	27	0	2	166	1	44	123
PACO-EBS	PACO-QBS	1	0	55	0	18	38	0	4	52	0	34	22	0	39	17	0	55	1	1	43	124	0	107	61

Mann-Whitey U test ($\alpha = 0.02$) comparison results for ACO algorithms ($-$ is better, $+$ is worse).

- ACS performs worst
- PACO with QBS rule performs best $\Rightarrow$ use from now on

Pheromone Initialization

- Utilize static information from problem instance to initialize pheromones for PACO-QBS

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Pheromone Initialization

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- Model service begin time b_i as random variable PD
- Define *VE* as a function which is larger if c_i and c_j are close and if c_j would be serviced at the end of its time window if visited directly after c_i

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		Instances with 25 customers						Instances with 50 customers						Instances with 100 customers						Total					
		f_1			f_2			f_1			f_2			f_1			f_2			f_1			f_2		
Algorithm 1 vs. 2		-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0
NoIni	Normal	0	2	54	4	26	26	4	7	45	6	32	18	8	14	34	4	32	20	12	23	133	14	90	64
NoIni	Power	0	3	53	1	33	22	2	7	47	3	35	18	5	13	38	4	34	18	7	23	138	8	102	58
NoIni	Uniform	0	2	54	1	39	16	1	7	48	4	40	12	3	15	38	2	42	12	4	24	140	7	121	40
Normal	Power	0	0	56	1	13	42	0	2	54	1	8	47	0	1	55	1	6	49	0	3	165	3	27	138
Normal	Uniform	0	0	56	0	19	37	0	3	53	1	13	42	0	3	53	0	15	41	0	6	162	1	47	120
Power	Uniform	0	0	56	4	0	52	0	0	56	3	1	52	0	0	56	9	0	47	0	0	168	16	1	151

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Algorithm 1 vs. 2		-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0	-	+	0
NoIni	Normal	0	2	54	4	26	26	4	7	45	6	32	18	8	14	34	4	32	20	12	23	133	14	90	64
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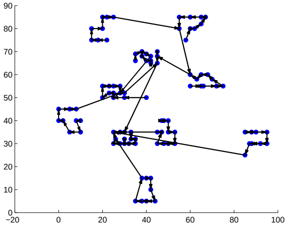
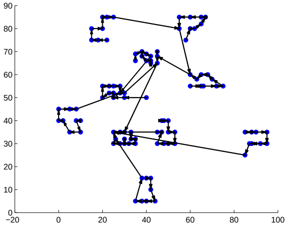
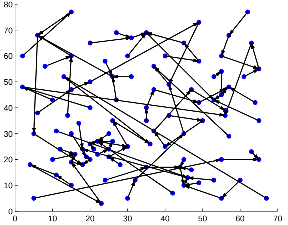


- Ideally, initialization should assign pheromones such that the edges with the strongest pheromones form larger tour components
- This works especially for instances where customers are clustered, but not if customers and time windows are completely random





Improved Initialization

- Ideally, initialization should assign pheromones such that the edges with the strongest pheromones form larger tour components
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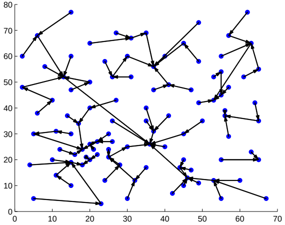
- Method 1: Change *VE* to put more pheromones on shorter edges



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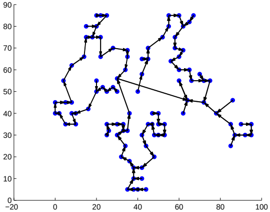

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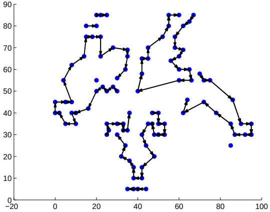

maximum selection

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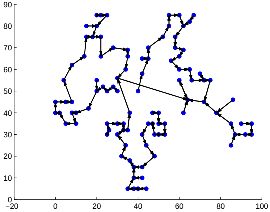

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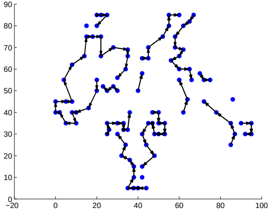

difference selection

中国科学技术大学 University of Science and Technology of China

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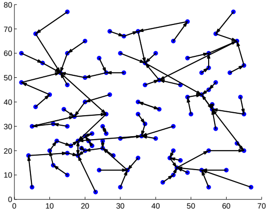

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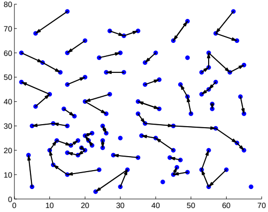

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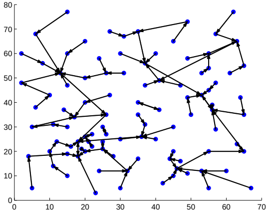

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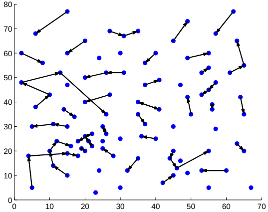

difference selection

Hybridize with Local Search

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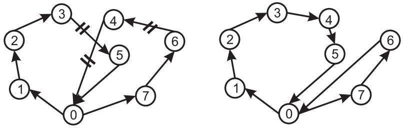
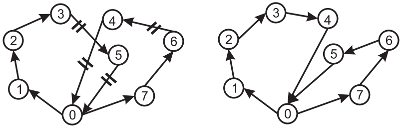
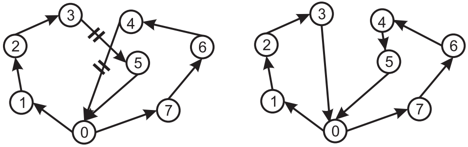


$N_{1-insert}$



$N_{1-exchange}$



N_{2-opt}

Hybridize with Local Search

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- Hybrid PI-PACO with difference selection achieves better results than hybrid PACO without pheromone initialization

Type	Goal	Chen and Ting [14]	Sodsoon and Changyom [22]	hybrid PACO	hybrid PI-PACO maximum selection	hybrid PI-PACO difference selection
R1	f_1	12.83	13.83	12.83	12.92	**12.75**
	f_2	1203.56	1259.19	1204.06	1205.11	1203.67
C1	f_1	**10**	**10**	**10**	**10**	**10**
	f_2	828.76	838.12	828.61	828.60	**828.55**
RC1	f_1	12.50	12.63	12.75	12.63	**12.38**
	f_2	1363.84	1436.58	1381.42	1380.78	1380.54
R2	f_1	**3.09**	3.82	3.45	3.64	3.54
	f_2	**932.23**	980.98	1005.35	995.03	1006.38
C2	f_1	**3**	**3**	3	**3**	**3**
	f_2	**589.86**	591.13	590.71	589.93	**589.86**
RC2	f_1	**3.75**	4.5	4.13	4.38	4.13
	f_2	**1079.81**	1141.63	1113.59	1156.20	1109.8

- Homberger and Gehring [12] proposed a hybrid metaheuristic
- We adopt this mechanism into PI-PACO.
- Hybrid PI-PACO with difference selection achieves better results than hybrid PACO without pheromone initialization
- It outperforms the hybrid algorithm by Chen and Ting [14] on problem type C1 and achieves similar results on problem type C2

Type	Goal	Chen and Ting [14]	Sodsoon and Changyom [22]	hybrid PACO	hybrid PI-PACO maximum selection	hybrid PI-PACO difference selection
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- We adopt this mechanism into PI-PACO.
- Hybrid PI-PACO with difference selection achieves better results than hybrid PACO without pheromone initialization
- It is similar to the MMAS-VRPTW [22] but outperforms it on all except R2 instances in terms of the distance

Type	Goal	Chen and Ting [14]	Sodsoon and Changyom [22]	hybrid PACO	hybrid PI-PACO maximum selection	hybrid PI-PACO difference selection
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Summary

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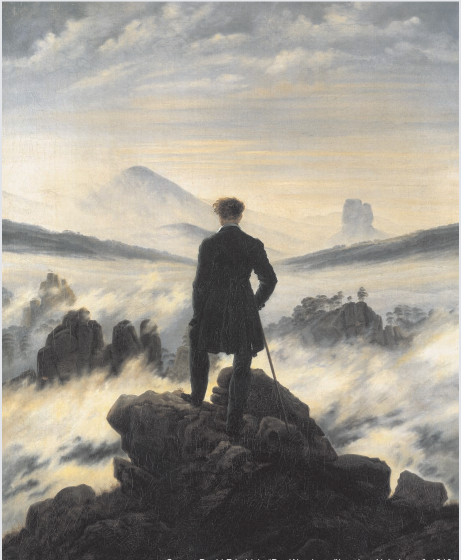
Summary

- PACO best ACO for VRPTW
- Pheromone matrix initialization makes it better
- Hybridization + pheromone matrix initialization is best
- Concept should be tested in offer domains, such as quadratic assignment poblems

谢谢！

Thank you.

Wei Shi[1], Thomas Weise[1], Raymond Chiong[2], and Bülent Çatay[3]
[1] University of Science and Technology of China,
[2] The University of Newcastle, Australia
[3] Sabanci University, Turkey



Caspar David Friedrich, “Der Wanderer über dem Nebelmeer”, 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog

Bibliography

Bibliography I

1. Olli Bräysy and Michel Gendreau. Vehicle routing problem with time windows, part ii: Metaheuristics. *Transportation Science*, 39(1):119–139, 2005.
2. Jean Berger and Mohamed Barkaoui. A parallel hybrid genetic algorithm for the vehicle routing problem with time windows. *Computers and Operations Research*, 31(12):2037–2053, 2004.
3. Jean-Yves Potvin and Samy Bengio. The vehicle routing problem with time windows part ii: Genetic search. *INFORMS Journal on Computing*, 8(2):165–172, 1996.
4. Luca Maria Gambardella, Éric Taillard, and Giovanni Agazzi. Macs-vrptw: A multiple ant colony system for vehicle routing problems with time windows. In D. Corne, M. Dorigo, and F. Glover, editors, *New Ideas in Optimization*. McGraw-Hill, London, U.K., 1999.
5. Haibing Li and Andrew Lim. Local search with annealing-like restarts to solve the VRPTW. *European Journal of Operational Research*, 150(1):115–127, 2003.
6. Wen-Chyuan Chiang and Robert A. Russell. Simulated annealing metaheuristics for the vehicle routing problem with time windows. *Annals of Operations Research*, 63(1):3–27, 1996.
7. Jörg Homberger and Hermann Gehring. Two evolutionary metaheuristics for the vehicle routing problem with time windows. *Information Systems and Operational Research*, 37:297–318, 1999.
8. Philippe Badeau, François Guertin, Michel Gendreau, Jean-Yves Potvin, and Eric Taillard. A parallel tabu search heuristic for the vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies*, 5(2):109–122, 1997.
9. Robert A. Russell. Hybrid heuristics for the vehicle routing problem with time windows. *Transportation Science*, 29(2): 156–166, 1995.
10. David Pisinger and Stefan Ropke. A general heuristic for vehicle routing problems. *Computers and Operations Research*, 34 (8):2403–2435, 2007.
11. Louis-Martin Rousseau, Michel Gendreau, and Gilles Pesant. Using constraint-based operators to solve the vehicle routing problem with time windows. *Journal of Heuristics*, 8(1):43–58, 2002.
12. Jörg Homberger and Hermann Gehring. A two-phase hybrid metaheuristic for the vehicle routing problem with time windows. *European Journal of Operational Research*, 162(1):220–238, 2005.
13. Jörg Homberger and Hermann Gehring. A two-phase hybrid metaheuristic for the vehicle routing problem with time windows. *European Journal of Operational Research*, 162(1):220–238, 2005.

14. Chia-Ho Chen and Ching-Jung Ting. A hybrid ant colony system for vehicle routing problem with time windows. *Journal of the Eastern Asia Society for Transportation Studies*, 6:2822–2836, 2005.
15. Fuh-Hwa Franklin Liu and Sheng-Yuan Shen. A route-neighborhood-based metaheuristic for vehicle routing problem with time windows. *European Journal of Operational Research*, 118:485–504, 1999.
16. Thomas Stützle and Holger H. Hoos. Max-min ant system. *Future Generation Computer Systems*, 16(8):889–914, 2000.
17. Marco Dorigo and Luca Maria Gambardella. Ant colony system: A cooperative learning approach to the traveling salesman problem. *IEEE TEVC*, 1(1), 1997.
18. Wei Shi and Thomas Weise. An initialized aco for the vrptw. In *Proc. of the 14th Intl. Conf. on Intelligent Data Engineering and Automated Learning*, pages 93–100, Hefei, China, October 20–23, 2013. Springer.
19. Michael Guntsch and Martin Middemdorf. A population based approach for aco. In *Applications of Evolutionary Computing*, volume 2279 of *Lecture Notes in Computer Science*, pages 72–81, Kinsale, Ireland, April 2002. Springer.
20. Sabrina Oliveira, Mohamed Saifullah Hussin, and Thomas Stützle. A detailed analysis of the population-based ant colony optimization algorithm for the TSP and the QAP. Technical Report 006, Université Libre de Bruxelles, IRIDIA, Bruxelles, Belgium, 2011.
21. Marius M. Solomon. Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research*, 35(2):254–265, 1987.
22. Suphan Sodsoon and Preecha Changyom. Max-min ant system (mmas) for vehicle routing problem with time windows. *KKU Engineering Journal*, 38(3):313–323, 2011.