Breakout local search for the traveling salesman problem with job-times

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Mots-clés : *Heuristics, routing-assignment problems, local search.*

1 Introduction

The Traveling Salesman Problem with Job-times (TSPJ) [5] combines the traveling salesman problem (TSP) and the scheduling problem. In this problem, a traveler starts from the depot 0, visits n given locations, and returns to the depot. For each visited location l, one job j among n given jobs with location-dependent processing times (job-times) jt_{lj} is assigned and the job starts to run during that time while the traveler moves to the next location. For a given job j assigned to location l, its completion time equals the travel-time from the depot 0 to location l plus the processing time jt_{lj}. For a Hamiltonian tour with the n job-location assignment, the completion time of the n jobs is the maximum completion time among the n jobs. The goal of the TSPJ is then to minimize the maximum completion time among the n jobs.

Introduced in [5], the TSPJ is a relevant model that can be used to formulate a variety of practical scenarios including autonomous robotics [2], equipment maintenance [6], and disaster recovery [1].

2 Breakout local search for TSPJ

We propose a heuristic algorithm for the TSPJ, which is based on the general breakout local search method [3]. The BLS algorithm iterates a dedicated local search procedure to find high-quality local optimal solutions and an adaptive perturbation procedure to escape local optimum traps. It employs an adaptive multi-perturbation strategy to reach a suitable search diversification by dynamically determining the number of perturbation moves for different types of perturbation.

In the local search phase, our BLS algorithm for TSPJ employs a dedicated tabu search [4] procedure exploring two complementary neighborhoods reinforced with a neighborhood reduction technique. When the search is judged to be stagnating, the perturbation phase is triggered with the given perturbation length ; BLS mixes two types of perturbations : informed perturbation (guided by historical search information related to move frequencies) and random perturbation, which are run with an equal probability.

3 Computational results

BLS is assessed on four sets of 310 instances with different sizes introduced in [5]. To ensure a fair comparison, we faithfully re-implemented the reference algorithms in [5] (denoted by Pro.I, Pro.II, Pro.III and Pro.IV). We accomplished an experimental comparison between BLS and the algorithms in [5] under a fair stopping condition. We additionally run BLS with a relaxed stopping condition. Each algorithm was run 10 times independently to solve each instance with distinct random seeds. The comparative results of BLS and the four reference algorithms are summarized in Table 1. In Table 1, the first column indicates the benchmark set. Column 2 presents the cut-off time running by our BLS. Column 3 shows the compared algorithms including the best-known solutions (BKS). Columns 4 - 6 indicate the number of instances for which BLS obtains a better, equal, or worse f_{best} value compared to each reference algorithm. The p-values from the Wilcoxon singned-rank test on f_{best} values over the instances from the same set are shown in column 7. From Table 1, we observe that our BLS algorithm performs extremely well compared to the reference algorithms from [5]. In particular, BLS discovers 291 record-breaking results (new upper bounds) out of the 310 instances while matching the best-known results for 16 other instances.

TAB. 1 – Summary of the number of instances where BLS reports a better (W), equal (T) or worse (L) f_{best} value compared to the results in [5] including the p-values from the Wilcoxon singed-rank test on the benchmark sets between BLS and each reference algorithm Pro.I, Pro.II, Pro.III and Pro.IV.

Instance	Cut-off time(s)	Pair algorithms	W	T	L	p-value
Set I	-	BLS vs. BKS	9	1	0	0.0077
		BLS vs. Pro.I	9	1	0	0.0077
		BLS vs. Pro.II	10	0	0	0.0020
		BLS vs. Pro.III	9	1	0	0.0077
		BLS vs. Pro.IV	9	1	0	0.0077
Set II	0.0012	BLS vs. BKS	46	18	36	0.6662
		BLS vs. Pro.I	80	13	7	2.389e-12
		BLS vs. Pro.II	69	7	29	1.384e-4
		BLS vs. Pro.III	76	16	8	8.332e-12
		BLS vs. Pro.IV	79	11	10	3.58e-12
Set III	2.19	BLS vs. BKS	98	0	2	4.5e-18
		BLS vs. Pro.I	100	0	0	3.876e-18
		BLS vs. Pro.II	98	0	2	4.371e-17
		BLS vs. Pro.III	100	0	0	3.877e-18
		BLS vs. Pro.IV	100	0	0	3.877e-18
Set IV	33.93	BLS vs. BKS	97	0	3	9.246e-17
		BLS vs. Pro.I	99	0	1	4.874e-17
		BLS vs. Pro.II	98	0	2	8.479e-16
		BLS vs. Pro.III	99	0	1	5.166e-17
		BLS vs. Pro.IV	98	0	2	5.399e-17
Set II	30	BLS vs. BKS	84	15	1	1.363e-15
		BLS vs. Pro.I	91	8	1	8.58e-17
		BLS vs. Pro.II	97	3	0	1.13e-17
		BLS vs. Pro.III	88	11	1	2.754e-16
		BLS vs. Pro.IV	91	8	1	1.231e-16
Set III	50	BLS vs. BKS	99	0	1	3.98e-18
		BLS vs. Pro.I	100	0	0	3.881e-18
		BLS vs. Pro.II	99	0	1	3.998e-18
		BLS vs. Pro.III	100	0	0	3.882e-18
		BLS vs. Pro.IV	100	0	0	3.883e-18
Set IV	70	BLS vs. BKS	99	0	1	7.547e-17
		BLS vs. Pro.I	99	0	1	3.186e-19
		BLS vs. Pro.II	99	0	1	7.548e-17
		BLS vs. Pro.III	99	0	1	3.234e-17
		BLS vs. Pro.IV	99	0	1	2.711e-17

Références

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