The XL instances for the Capacitated Vehicle Routing Problem

Eduardo Queiroga, Rafael Martinelli, Anand Subramanian,
Eduardo Uchoa, Thibaut Vidal

January 12th, 2026

1 Introduction

The Capacitated Vehicle Routing Problem (CVRP), the first [10] and most canonical vehicle routing variant, is among the most widely studied problems in combinatorial optimization and operations research. Over the last decades, a large body of algorithmic research on the CVRP has been supported by publicly available benchmark instance sets. In 2014, Uchoa et al. [22] observed that the then-existing sets ABEFGMPT [8, 12, 6, 20, 13] were either: (i) too easy for the contemporary algorithms; (ii) too artificial; or (iii) too homogeneous, failing to capture the wide range of characteristics encountered in real-world applications. To address these limitations, they proposed the X set, composed of 100 instances ranging from 100 to 1,000 customers and carefully designed to provide a comprehensive and diverse experimental testbed.

- The X set, as well as all other major CVRP benchmark sets, was made available in the CVRPLib (`https://galgos.inf.puc-rio.br/cvrplib/`). This web repository includes a graphical visualization tool and maintains an updated Best Known Solution (BKS) for each instance.
- This set rapidly became the primary benchmark for evaluating new algorithms, both exact and heuristic, triggering extensive subsequent work. As of today, 61 out of the original 100 X instances have proven optimal solutions. The last improved BKS for an instance in that set was reported in June 2021.
- This set also served as the basis for the CVRP track of the 12th DIMACS Implementation Challenge (2021–2022) [1]. The best CVRP heuristics available at that time, all based on classic OR techniques such as local search and metaheuristics, were evaluated and compared.

Over the past decade, following a highly promising trend in general optimization, numerous machine-learning-based heuristics have emerged for vehicle routing problems. Some of them are currently the best performers for stochastic and dynamic variants, such as the winners of the dynamic VRPTW track at the EURO Meets NeurIPS 2022 VRP Competition [2]. However, only very recently have some ML-based (often hybrid) methods reached a performance level comparable to that of the best classical methods on deterministic variants such as the CVRP (e.g., [14]). Nevertheless, as early as 2021, Queiroga et al. [19] pointed out that ML approaches for the CVRP were rarely evaluated on standard benchmark sets. Instead, many works relied on ad hoc instance generators designed primarily to produce labeled data, often in a simplistic manner that hindered experimental comparisons. To address this gap, they introduced the XML (X instances for Machine Learning) set.

- The XML set consists of 10,000 instances with 100 customers, corresponding to the instance size most commonly used for ML-based CVRP methods at the time. The instances follow a generation scheme similar to that of the X set and are highly diverse, systematically covering most characteristics encountered in practice.
- All 10,000 XML instances have known optimal solutions. This allows the measurement of *absolute errors* (differences with respect to the optimum) rather than *relative errors* (differences with respect to a reference method). Indeed, relative errors could be particularly misleading due to another issue

in many early ML articles on the CVRP: the use of inferior methods as references. The knowledge of optimal solutions has another advantage when doing extensive evaluations of methods: a run can be stopped as soon as the optimal value is reached, saving computational resources.

- Beyond evaluation, ML-based methods require large quantities of instances for training. Accordingly, the XML set was released together with a Python script that can be used to generate an arbitrary number of statistically similar training instances.

Despite these advantages, the XML set has not yet achieved the same level of systematic use in the domain as the X set. This is likely due to the different experimental and domain-specific practices that were established early in the development of ML methods.

Finally, two benchmark sets containing larger-scale instances with more than 1,000 customers have been proposed. Arnold et al. [5] introduced what we refer to as the AGS set, composed of 10 instances ranging from 3,000 to 30,000 customers and reflecting real-world parcel delivery operations in Belgium. More recently, Accorsi and Vigo [4] proposed a collection of 20 very large instances, ranging from 20,000 to 1,000,000 customers. These AV instances were generated by projecting the geographical coordinates of randomly sampled addresses from various Italian regions onto the Euclidean plane.

The AGS and AV sets are highly valuable for the CVRP community. Indeed, various delivery companies face large-scale problems and require algorithms capable of handling thousands of customers, necessitating suitable benchmark sets within that range. However, those existing large-instance sets are limited in their number and diversity. Notably, all those 30 Belgian and Italian instances have customer demands sampled from the uniform discrete distribution $UD[1,3]$ (i.e., values in $\{1,2,3\}$ with equal probability). Besides this, the existing sets leave the crucial range from 1,001 to 2,999 customers empty (the AGS set includes instances with 3,000, 4,000, 6,000, and 7,000 customers).

In light of these observations, and roughly a decade after the introduction of the X instances by Uchoa et al. [22], we argue that it is timely to extend this benchmark family with an additional XL set composed of 100 instances ranging from 1,000 to 10,000 customers. The XL instances are designed to systematically cover a wide range of instance attributes, following the same principles that guided the construction of the original X set. This introduction also provides an opportunity to analyze the performance of algorithms designed to address instances within that range, stimulate research in this area through an active competition, and point out future research directions.

2 Generation of the XL Instances

The XL instances were generated following a scheme very similar to that first proposed in Uchoa et al. [22] (X instances) and also used in [19] (XML instances), producing two-dimensional Euclidean instances with integer coordinates on a $[0,1000] \times [0,1000]$ grid with the following attributes:

- **Depot positioning**: *Random* (R), *Central* (C), point (500,500), or *Eccentric* (E), point (0,0).
- **Customer positioning**: *Random* (R), *Clustered* (C), or *Random-Clustered* (RC). The clusters are formed over a number (taken from $UD[2,6]$) of randomly distributed seed customers that attract other customers with an exponential decay, mimicking the densities found in some large urban agglomerations that have grown from more or less isolated original nuclei.
- **Demand distribution**:
  - *Unitary* (U).
  - *Small values, large coefficient of variation (CV)* (1–10): demands sampled from $UD[1,10]$.
  - *Small values, small CV* (5–10): demands sampled from $UD[5,10]$.
  - *Large values, large CV* (1–100): demands sampled from $UD[1,100]$.
  - *Large values, small CV* (50–100): demands sampled from $UD[50,100]$.
  - *Depending on quadrant* (Q): demands sampled from $UD[1,50]$ if the customer lies in an even quadrant with respect to $(500,500)$, and from $UD[51,100]$ otherwise.

- *Many small values, few large values* (SL): most demands sampled from $UD[1, 10]$, with the remaining demands sampled from $UD[50, 100]$.

- **Average route size** r: *Ultra short* (r from $U[3, 5]$), *Very short* (r from $U[5, 8]$), *Short* (r from $U[8, 12]$), *Medium* (r from $U[12, 16]$), *Long* (r from $U[16, 25]$), *Very long* (r from $U[25, 50]$), and *Ultra long* (r from $U[50, 200]$). The inclusion of instances with ultra long routes was demand from a number of users of the X and XML sets who remarked that some real-world delivery companies were already operating routes in that range.

The name of an instance follows the standard adopted in the ABEFMPX sets and has the format XL-nA-kB, where A denotes the total number of points including the depot, and B represents the minimum possible number of routes $K_{\min}$. Those values are obtained by the exact solution of a Bin Packing Problem. It should be emphasized that, as in the X and XML sets, $K_{\min}$ serves only as a reference, and solutions using more routes are permitted.

Table 1 summarizes the attributes of each XL instance. When Customer Positioning is C or RC, the number in brackets is the number of seeds. Column Q is the vehicle capacity and column r is the average route size, assuming solutions having $K_{\min}$ routes. Column BKS is the Best Known Solution and the Method that found it during the experiments described in Section 4. The Python generator for the new XL instances, which can be used to generate many other statistically similar instances, is publicly available in the CVRPLib. Further details on the instance generation process can be found in Uchoa et al. [22].

3 CVRPLib Best Known Solution Challenge

One of the most distinctive features of the X set is the availability of high-quality BKSs that have been progressively established over time. Proven optimal solutions were obtained for 61 out of 100 instances using branch-cut-and-price algorithms [16, 17, 21, 24], which incorporate techniques developed by many authors over several decades (see [18, 9]). It is widely believed that most BKSs for the remaining 39 instances are also optimal, and that the few non-optimal BKSs are only a few units (corresponding to less than 0.01%) away from the true optimum. Those beliefs stem from the fact that long computational runs of several powerful algorithms were applied to these instances, particularly during the DIMACS Challenge, without yielding any further improvements since June 2021. As a consequence, when a new method reports a certain average gap with respect to the BKSs of the X set, this value is generally expected to be a very close approximation of the true optimality gap.

Our objective is to achieve a comparable level of BKS quality for the newly introduced XL set. This goal motivated the creation of the *CVRPLib Best Known Solution (BKS) Challenge*, a community-wide computational competition designed to stimulate the discovery of extremely high-quality initial solutions for the XL instances. The BKS Challenge is a 30-day competition that starts on January 12th, 2026, coinciding with the public release of the XL instance set. During this period, participating teams are invited to submit improved feasible solutions for any of the 100 XL instances. All submitted solutions are automatically verified by the CVRPLib platform for feasibility and objective value. For each instance, the platform maintains a live record of the BKS and the team currently holding it.

The challenge adopts a *lead-time-based scoring system*, schematically depicted in Figure 1. Whenever a team submits a solution that improves the current BKS of an instance, that team starts accumulating a score (measured in days) proportional to the amount of time during which its solution remains unbeaten. If another team later improves the solution, the accumulation of lead time stops. At the end of the competition, an additional 5-day bonus is awarded to the team holding the final BKS for each instance. The overall ranking is determined by summing the scores obtained across all instances. The challenge features two public leaderboards. The first one tracks, for each instance, the chronological evolution of their BKSs and the teams responsible for them. The second is a global leaderboard, aggregating the scores obtained over all instances. Instances for which no improvement over the initial BKS is achieved do not contribute to the global score. More information about the competition and its detailed set of rules can be found in `https://galgos.inf.puc-rio.br/cvrplib/en/bks_challenge/overview`.

Before the start of the competition, the organizers devoted substantial computational effort to finding some high-quality initial BKSs for all XL instances. Existing state-of-the-art methods for large-scale

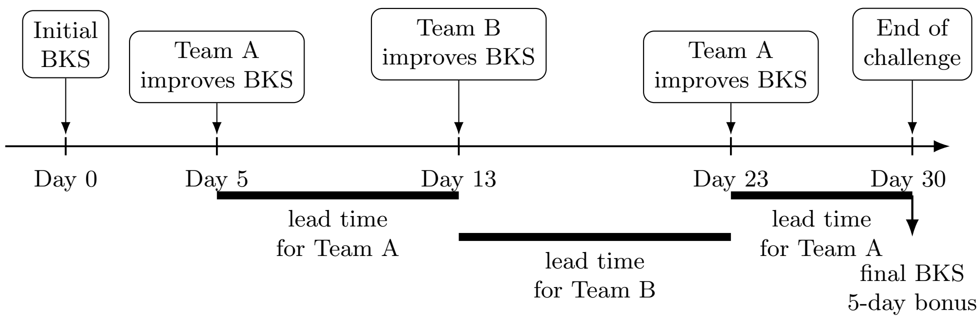

Figure 1: Timeline and lead-time scoring mechanism of the CVRPLib Best Known Solution Challenge for a single instance. In that illustrative example, Team A would receive a score of $8 + 7 + 5 = 20$ days, and Team B would receive 10 days.

problems, all with publicly available source code, were run with multiple random seeds to ensure that the initial BKSs already represent a strong baseline. As a result, improving these solutions during the challenge requires genuine algorithmic advances, making the competition both demanding and scientifically meaningful.

4 Initial BKSs for the XL instances and Experiments

Table 1: Description of the new set XL of large-scale instances, along with the initial BKSs that will be used in the Challenge.

#	Name	Dep	Cust	Dem	Q	r	BKS	Method
1	XL-n1048-k237	E	R	SL	128	4.7	380,211	AILS-II
2	XL-n1094-k157	C	C (6)	U	7	7.8	112,431	AILS-II
3	XL-n1141-k112	R	RC (3)	50–100	761	10.2	95,727	AILS-II
4	XL-n1188-k96	R	RC (3)	Q	782	12.4	104,415	AILS-II
5	XL-n1234-k55	E	R	1–10	126	22.7	96,647	AILS-II
6	XL-n1281-k29	C	C (5)	1–100	2,267	45.5	31,101	FILO2
7	XL-n1328-k19	R	RC (3)	5–10	542	72.6	38,247	FILO
8	XL-n1374-k278	C	R	Q	248	4.9	233,049	AILS-II
9	XL-n1421-k232	E	C (4)	1–100	309	6.1	384,826	AILS-II
10	XL-n1468-k151	E	R	50–100	726	9.7	250,166	AILS-II
11	XL-n1514-k106	C	RC (4)	5–10	107	14.2	92,425	AILS-II
12	XL-n1561-k75	R	C (4)	U	21	21.9	101,549	AILS-II
13	XL-n1608-k39	C	RC (3)	SL	337	42.1	48,021	AILS-II
14	XL-n1654-k11	E	R	1–10	845	155.4	36,385	AILS-II
15	XL-n1701-k562	R	C (6)	50–100	227	3	521,136	AILS-II
16	XL-n1748-k271	R	C (3)	Q	270	6.4	173,896	AILS-II
17	XL-n1794-k163	C	R	U	11	11.2	141,729	AILS-II
18	XL-n1841-k126	E	RC (2)	SL	186	14.6	214,038	AILS-II
19	XL-n1888-k82	E	R	5–10	173	23.1	143,623	AILS-II
20	XL-n1934-k46	C	C (6)	1–100	2,166	42.2	53,013	AILS-II
21	XL-n1981-k13	R	RC (2)	1–10	832	153.5	32,580	AILS-II
22	XL-n2028-k617	C	C (6)	50–100	247	3.3	544,403	AILS-II
23	XL-n2074-k264	E	R	1–100	401	7.8	421,627	AILS-II
24	XL-n2121-k186	R	RC (5)	1–10	62	11.4	283,211	AILS-II
25	XL-n2168-k138	C	R	Q	800	15.7	127,298	AILS-II
26	XL-n2214-k131	R	C (5)	U	17	17.8	154,676	AILS-II
27	XL-n2261-k54	E	RC (5)	5–10	319	42.5	98,907	AILS-II

Continued on next page

#	Name	Dep	Cust	Dem	Q	r	BKS	Method
28	XL-n2307-k34	C	R	SL	479	69.6	47,958	AILS-II
29	XL-n2354-k631	E	C (4)	5–10	28	3.7	940,825	AILS-II
30	XL-n2401-k408	R	RC (4)	Q	303	5.9	463,473	AILS-II
31	XL-n2447-k290	C	RC (2)	SL	150	8.4	218,706	AILS-II
32	XL-n2494-k194	E	C (2)	1–100	661	12.9	361,205	AILS-II
33	XL-n2541-k121	R	R	U	21	21.7	146,390	AILS-II
34	XL-n2587-k66	C	R	50–100	2,986	39.6	73,394	FILO2
35	XL-n2634-k17	R	C (4)	1–10	898	162.6	31,641	FILO2
36	XL-n2681-k540	E	RC (3)	1–100	251	5	798,603	AILS-II
37	XL-n2727-k546	C	RC (5)	U	5	5.3	431,134	AILS-II
38	XL-n2774-k286	E	C (5)	50–100	731	9.7	407,847	AILS-II
39	XL-n2821-k208	R	R	SL	179	13.5	216,763	AILS-II
40	XL-n2867-k120	R	C (4)	5–10	180	23.9	165,990	AILS-II
41	XL-n2914-k95	C	RC (3)	Q	1,663	30.8	88,990	AILS-II
42	XL-n2961-k55	E	R	1–10	297	53.8	108,084	AILS-II
43	XL-n3007-k658	C	R	1–10	25	4.4	522,319	AILS-II
44	XL-n3054-k461	E	RC (4)	50–100	497	6.6	782,739	AILS-II
45	XL-n3101-k311	R	C (3)	SL	159	10	245,937	AILS-II
46	XL-n3147-k232	R	RC (6)	5–10	102	13.6	256,626	AILS-II
47	XL-n3194-k161	C	R	Q	1,012	19.9	148,728	AILS-II
48	XL-n3241-k115	E	C (4)	1–100	1,404	28.3	221,370	AILS-II
49	XL-n3287-k30	C	C (2)	U	111	112	40,229	AILS-II
50	XL-n3334-k934	E	R	1–10	20	3.5	1,452,698	AILS-II
51	XL-n3408-k524	R	RC (3)	Q	353	6.5	678,643	AILS-II
52	XL-n3484-k436	E	C (6)	U	8	8.2	703,355	AILS-II
53	XL-n3561-k229	C	RC (5)	1–100	779	15.6	209,386	AILS-II
54	XL-n3640-k211	R	R	5–10	130	17.2	189,724	AILS-II
55	XL-n3721-k77	E	RC (2)	SL	371	48.8	162,862	AILS-II
56	XL-n3804-k29	C	R	50–100	10,064	134	52,885	AILS-II
57	XL-n3888-k1010	R	C (2)	SL	128	4.2	1,880,368	AILS-II
58	XL-n3975-k687	C	RC (4)	1–10	32	5.6	525,901	AILS-II
59	XL-n4063-k347	E	R	Q	598	11.7	548,931	AILS-II
60	XL-n4153-k291	R	C (3)	1–100	726	14.3	356,034	AILS-II
61	XL-n4245-k203	R	R	U	21	21	229,659	AILS-II
62	XL-n4340-k148	E	RC (6)	50–100	2,204	29.3	244,226	AILS-II
63	XL-n4436-k48	C	C (4)	5–10	706	94.1	61,477	AILS-II
64	XL-n4535-k1134	R	C (4)	U	4	4.3	1,203,566	AILS-II
65	XL-n4635-k790	C	RC (4)	1–100	294	5.9	610,650	AILS-II
66	XL-n4738-k487	E	R	Q	499	9.7	760,501	AILS-II
67	XL-n4844-k321	R	R	SL	188	15.1	404,652	AILS-II
68	XL-n4951-k203	E	RC (5)	50–100	1,848	24.5	285,269	AILS-II
69	XL-n5061-k184	C	C (5)	5–10	206	27.4	161,629	AILS-II
70	XL-n5174-k55	C	C (6)	1–10	520	94.1	61,382	AILS-II
71	XL-n5288-k1246	E	R	50–100	318	4.2	1,960,101	AILS-II
72	XL-n5406-k783	R	RC (2)	1–10	38	6.8	1,040,536	AILS-II
73	XL-n5526-k553	R	C (3)	U	10	10	336,898	AILS-II
74	XL-n5649-k401	E	R	SL	181	14.1	644,866	AILS-II
75	XL-n5774-k290	C	RC (4)	1–100	1,012	19.9	250,207	AILS-II
76	XL-n5902-k122	E	RC (3)	Q	2,663	48.8	217,447	AILS-II
77	XL-n6034-k61	R	C (5)	5–10	744	98.9	64,448	FILO2
78	XL-n6168-k1922	C	R	1–100	162	3.2	1,530,010	AILS-II
79	XL-n6305-k1042	R	RC (2)	Q	268	6	1,177,528	AILS-II
80	XL-n6445-k628	E	R	5–10	77	10.2	996,623	AILS-II
81	XL-n6588-k473	C	C (4)	1–10	76	13.8	334,068	AILS-II
82	XL-n6734-k330	R	RC (2)	50–100	1,534	20.4	448,031	AILS-II
83	XL-n6884-k148	E	C (4)	SL	357	46.4	181,809	AILS-II

Continued on next page

#	Name	Dep	Cust	Dem	Q	r	BKS	Method
84	XL-n7037-k38	C	R	U	187	187.1	70,845	AILS-II
85	XL-n7193-k1683	E	RC (2)	5–10	32	4.2	2,958,979	AILS-II
86	XL-n7353-k1471	R	R	U	5	5.1	1,537,811	AILS-II
87	XL-n7516-k859	C	C (2)	1–100	439	8.8	573,902	AILS-II
88	XL-n7683-k602	R	RC (3)	50–100	957	12.8	702,098	AILS-II
89	XL-n7854-k365	E	C (2)	SL	223	21.5	659,221	AILS-II
90	XL-n8028-k294	C	R	Q	1,386	27.3	266,900	AILS-II
91	XL-n8207-k108	C	C (2)	1–10	415	75.9	118,274	AILS-II
92	XL-n8389-k2028	E	RC (4)	1–100	208	4.1	3,358,731	AILS-II
93	XL-n8575-k1297	R	R	1–10	36	6.5	1,089,137	AILS-II
94	XL-n8766-k1032	R	RC (4)	50–100	637	8.5	906,406	AILS-II
95	XL-n8960-k634	E	C (5)	5–10	106	14.1	773,383	AILS-II
96	XL-n9160-k379	C	R	SL	237	24.2	324,092	AILS-II
97	XL-n9363-k209	C	RC (2)	U	45	45.2	205,575	FILO2
98	XL-n9571-k55	R	R	Q	8,773	174.7	106,791	FILO2
99	XL-n9784-k2774	E	C (4)	1–10	19	3.4	4,078,217	AILS-II
100	XL-n10001-k1570	E	RC (2)	50–100	479	6.4	2,333,757	AILS-II

All our experiments were run on a single thread of 2 x AMD EPYC 9654 (Zen 4) @ 2.40 GHz, 384MB cache L3 with 750G of RAM shared among up to 50 parallel executions, and running AlmaLinux 9.6. All these methods were run 60 times in each instance, using a different random number generator seed each time, stopping each run at a two-hour time limit. Therefore, the total time spent per instance was $60 \times 2 = 120$ hours, i.e., five days. The two-hour time limit is set to the same value previously used in the 12th DIMACS Challenge [1] for the larger CVRP instances of set X (ranging from 401 to 1000 customers). The tested methods were the following:

- KGLS$^{\text{XXL}}$ [5]: `https://github.com/ArnoldF/LocalSearchVRPXXL`. As the code does not have a parameter for the seed, the customers of an instance were shuffled before each run to obtain a different trajectory of the method.
- SISRs [7]: We had access to a faithful reimplementation of this algorithm [11] that obtains results statistically identical from the original one.
- FILO [3]: `https://github.com/acco93/filo`.
- FILO2 [4]: `https://github.com/acco93/filo2`.
- HGS-CVRP [23]: `https://github.com/vidalt/HGS-CVRP`. That code comes with an explicit disclaimer: "This code version has been designed and calibrated for medium-scale instances with up to 1,000 customers. It is not designed in its current form to run very-large scale instances."
- AILS-II [15]: `https://github.com/INFORMSJoC/2023.0106`.
- LKH-3 (3.0.13): `http://webhotel4.ruc.dk/~keld/research/LKH-3/`. Parameter `VEHICLES` was set to the known bound in the instance name, as LKH-3 requires a fixed number of vehicles. For 10 instances, none of the 60 runs found a feasible (penalty-free) solution within the two-hour time limit.
- Google OR-Tools (v9.10.4067): `https://developers.google.com/optimization/routing/cvrp`. We used the guided local search (GLS) configuration as recommended by the documentation to find superior solutions. The set of customers was also shuffled to obtain different trajectories for the different runs of an instance.

FILO, SISRs, HGS-CVRP, OR-Tools, and LKH-3 are coded in C/C++ and were compiled with g++ 12.3.1. AILS-II and KGLS$^{\text{XXL}}$ use Java OpenJDK 21.0.1.

Table 2 shows the results. For each method, column "Best" gives the best solution value found in all the 60 runs, and column "Mean" is the arithmetic mean of the solution values of each run. At the end of the table, row "Avg. gap" is the average gap (both for "Best" and "Mean") with respect to the overall BKSs (the best solution obtained by any method). Since the size of instances in the XL set spans a full order of magnitude, it is also interesting to have separate average results for the 50 instances with fewer than 3,400 customers and for the 50 instances with more customers.

We note that SISRs, HGS-CVRP, OR-Tools, and LKH-3 were not originally designed and calibrated for instances with up to 10,000 customers. We ran those methods without any parameter calibration on the new XL instances, and the chosen time limit relative to instance size (2 hours for up to 10,000 customers) is also significantly shorter than in earlier comparative studies (e.g., 2 hours for instances of up to 1,000 customers in the DIMACS Challenge, or a time budget proportional to the instance size with four minutes per 100 customers in Vidal 23). Therefore, alternative parameter settings—different from those originally proposed—or even simple methodological adaptations would lead to improved performance with respect to the results presented here. This is why the results obtained by those methods are grouped in the right of Table 2 and only presented as an indication.

Table 2: Results on XL instances: 60 independent runs per instance with a 2-hour time limit. Best results are shown in **bold** and second-best results are underlined.

	Large-scale methods								Standard-scale methods							
Instance	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
XL-n1048-k237	**380,211**	**380,369.4**	381,718	382,614.6	381,304	382,348.5	384,530	385,633.1	380,991	381,444.8	380,675	381,338.8	381,021	381,811.7	385,826	387,505.2
XL-n1094-k157	**112,431**	**112,452.6**	112,437	112,468.1	112,432	112,466.1	112,616	112,695.7	112,462	112,514.8	112,492	112,562.7	112,815	112,970.8	114,525	114,916.3
XL-n1141-k112	**95,727**	**95,798.9**	95,764	95,901.6	95,767	95,881.5	96,343	96,443.3	95,863	96,029.4	95,810	96,028.4	101,676	102,963.8	100,163	100,807.8
XL-n1188-k96	**104,415**	**104,511.6**	104,556	104,705.8	104,563	104,690.6	105,089	105,249.1	104,640	104,812.1	104,574	104,772.0	106,168	106,752.8	109,745	110,702.0
XL-n1234-k55	**96,647**	**96,787.3**	96,715	96,892.3	96,766	96,865.6	97,316	97,486.3	97,077	97,386.2	96,785	96,928.9	97,868	98,200.5	102,270	103,150.6
XL-n1281-k29	31,105	31,201.3	31,107	31,187.1	**31,101**	**31,174.1**	31,236	31,356.1	31,170	31,239.3	31,235	31,365.9	31,567	31,799.5	32,901	33,444.8
XL-n1328-k19	38,248	38,317.4	**38,247**	**38,315.0**	38,248	38,326.1	38,472	38,626.2	38,261	38,380.9	38,394	38,533.2	38,765	39,053.5	40,847	41,921.6
XL-n1374-k278	**233,049**	**233,248.0**	233,572	233,836.9	233,394	233,796.3	234,293	234,614.6	233,643	233,935.9	233,396	233,674.4	271,327	280,689.7	244,408	246,752.1
XL-n1421-k232	**384,826**	**384,949.2**	385,757	386,057.5	385,793	385,998.9	387,321	387,806.7	385,944	386,806.4	385,059	385,291.3	391,667	393,269.9	394,394	395,782.0
XL-n1468-k151	**250,166**	**250,305.2**	250,487	250,685.1	250,428	250,689.6	251,526	251,767.9	250,979	251,416.3	250,490	250,807.6	297,764	307,088.0	258,121	259,274.1
XL-n1514-k106	**92,425**	**92,489.7**	92,472	92,552.3	92,465	92,550.3	92,929	93,084.8	92,605	92,751.6	92,542	92,706.2	93,486	93,840.6	97,748	98,696.6
XL-n1561-k75	**101,549**	**101,583.3**	101,567	101,598.4	101,567	101,600.8	101,728	101,807.8	101,654	101,756.0	101,634	101,694.6	102,056	102,215.2	104,477	104,883.9
XL-n1608-k39	**48,021**	**48,064.3**	48,048	48,209.4	48,055	48,169.2	48,160	48,409.0	48,022	48,136.7	48,183	48,368.7	48,573	48,842.0	51,093	52,137.1
XL-n1654-k11	**36,385**	**36,429.1**	36,405	36,443.6	36,403	36,444.0	36,598	36,957.5	36,499	36,652.1	36,521	36,614.6	36,615	36,945.2	39,736	40,813.7
XL-n1701-k562	**521,136**	**521,380.5**	524,642	525,299.0	524,731	525,333.3	526,455	527,011.0	522,603	523,391.5	522,024	522,435.6	589,386	602,157.0	543,924	546,859.9
XL-n1748-k271	**173,896**	**174,027.2**	174,423	174,555.8	174,368	174,528.2	175,208	175,458.2	174,534	174,857.0	174,212	174,370.7	182,414	184,422.9	183,850	186,541.3
XL-n1794-k163	**141,729**	**141,777.6**	141,743	141,827.8	141,750	141,819.0	142,050	142,196.8	141,862	141,989.5	141,890	142,012.1	142,630	142,859.8	145,676	146,337.8
XL-n1841-k126	**214,038**	**214,142.6**	214,424	214,601.9	214,257	214,446.9	215,079	215,376.7	215,004	215,535.4	214,283	214,465.7	216,095	216,484.8	225,801	228,519.6
XL-n1888-k82	**143,623**	**143,733.5**	143,769	143,892.0	143,704	143,855.2	144,447	144,609.1	144,738	145,168.3	143,855	144,020.5	145,617	146,161.4	150,047	150,745.8
XL-n1934-k46	**53,013**	**53,067.3**	53,019	53,216.1	53,025	53,193.7	53,202	53,468.4	53,078	53,156.4	53,175	53,483.6	54,272	54,821.5	57,082	58,423.0
XL-n1981-k13	**32,580**	**32,639.1**	32,602	32,672.6	32,617	32,760.8	32,695	32,958.7	32,665	32,752.2	32,757	32,961.3	32,753	32,989.8	35,019	36,103.9
XL-n2028-k617	**544,403**	**544,596.6**	547,124	547,687.3	547,181	547,645.2	548,387	548,760.1	545,456	545,993.2	545,103	545,516.6	647,655	666,636.0	570,295	572,389.5
XL-n2074-k264	**421,627**	**421,805.0**	422,175	422,449.9	422,214	422,492.3	424,917	425,405.7	426,672	427,692.7	422,267	422,584.4	452,516	458,340.7	435,546	439,098.4
XL-n2121-k186	**283,211**	**283,323.6**	283,383	283,531.6	283,333	283,506.0	284,793	285,026.6	285,705	286,790.9	283,429	283,600.1	284,991	285,363.0	293,138	295,124.1
XL-n2168-k138	**127,298**	**127,450.2**	127,500	127,619.5	127,458	127,576.7	128,271	128,500.4	127,930	128,150.2	127,710	127,941.7	134,831	137,346.9	136,817	140,455.5
XL-n2214-k131	**154,676**	**154,722.4**	154,696	154,763.3	154,693	154,757.4	154,978	155,087.7	154,910	155,021.2	154,841	154,920.1	155,496	155,704.4	158,831	159,335.6
XL-n2261-k54	**98,907**	**98,993.6**	99,021	99,135.9	99,004	99,084.4	99,430	99,668.1	99,837	100,195.0	99,170	99,309.4	101,293	101,786.1	105,404	106,532.6
XL-n2307-k34	**47,958**	**48,020.2**	48,046	48,225.2	47,984	48,125.4	48,206	48,439.7	48,006	48,178.9	48,233	48,451.5	48,901	49,339.0	52,879	54,328.1
XL-n2354-k631	**940,825**	**940,960.9**	942,980	943,678.0	942,723	943,357.0	943,727	944,550.9	942,928	944,394.0	941,310	941,626.8	945,446	946,780.2	982,412	986,908.4
XL-n2401-k408	**463,473**	**463,673.4**	464,251	464,722.2	464,045	464,534.3	466,903	467,336.2	467,162	468,236.6	464,495	464,839.6	539,326	558,932.9	487,321	503,274.1
XL-n2447-k290	**218,706**	**218,821.4**	219,407	219,628.7	219,199	219,434.0	220,242	220,656.7	219,759	220,267.5	219,188	219,488.0	224,099	225,815.8	236,532	240,391.8
XL-n2494-k194	**361,205**	**361,273.1**	361,664	362,285.1	361,670	362,269.9	363,648	363,810.2	364,118	364,995.3	361,527	361,665.8	370,229	373,017.9	368,638	370,337.3
XL-n2541-k121	**146,390**	**146,489.1**	146,435	146,502.5	146,422	146,499.3	146,891	147,004.5	146,898	147,182.1	146,601	146,738.9	147,836	148,125.0	152,472	153,089.5
XL-n2587-k66	73,451	**73,520.7**	73,473	73,571.1	**73,394**	73,535.1	73,732	73,917.1	73,695	73,914.9	73,629	73,826.4	75,387	75,906.3	80,721	82,005.7
XL-n2634-k17	31,657	31,781.0	31,647	**31,748.6**	**31,641**	31,771.6	32,243	32,605.3	32,074	32,341.5	32,088	32,375.0	32,418	32,846.8	35,327	36,090.5
XL-n2681-k540	**798,603**	**798,950.4**	799,927	800,389.8	799,928	800,296.5	804,093	804,920.8	808,973	810,185.0	799,498	799,927.8	886,992	909,519.0	821,635	825,322.9
XL-n2727-k546	**431,134**	**431,173.0**	431,147	431,205.1	431,152	431,193.6	431,697	431,834.0	431,443	431,618.2	431,320	431,483.8	432,092	432,335.8	434,453	434,942.4
XL-n2774-k286	**407,847**	**408,000.2**	408,760	408,941.9	408,678	408,865.7	409,993	410,307.4	411,338	412,003.4	408,428	408,696.3	425,420	428,405.3	418,746	419,972.9
XL-n2821-k208	**216,763**	**216,868.8**	217,368	217,614.4	217,222	217,391.0	218,149	218,567.7	218,225	218,674.3	217,249	217,588.1	219,884	220,864.7	236,961	241,288.1
XL-n2867-k120	**165,990**	**166,056.6**	166,130	166,213.8	166,081	166,209.0	166,738	166,939.6	168,024	168,613.2	166,236	166,364.1	169,287	170,659.0	172,143	173,205.9
XL-n2914-k95	**88,990**	**89,080.2**	89,091	89,178.4	89,064	89,149.8	89,575	89,861.4	89,573	89,804.5	89,433	89,655.6	92,263	92,914.7	97,062	100,665.0
XL-n2961-k55	**108,084**	**108,200.9**	108,211	108,370.2	108,199	108,306.9	108,941	109,169.3	109,841	110,343.8	108,531	108,701.8	112,122	112,864.4	119,044	120,361.9
XL-n3007-k658	**522,319**	**522,458.9**	522,613	522,812.4	522,516	522,720.1	524,744	525,157.3	525,139	526,498.3	522,717	522,945.1	527,958	528,972.3	541,406	544,250.3

Continued on next page

Instance	Large-scale methods								Standard-scale methods							
	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
XL-n3054-k461	**782,739**	**783,022.3**	784,471	784,883.9	784,423	784,754.7	786,510	787,008.0	791,047	791,893.7	783,889	784,227.6	896,002	911,867.1	809,515	811,540.9
XL-n3101-k311	**245,937**	**246,059.9**	246,366	246,627.0	246,264	246,444.4	247,072	247,375.9	247,189	247,858.2	246,421	246,652.6	252,244	253,877.6	260,864	264,149.3
XL-n3147-k232	**256,626**	**256,746.6**	256,838	257,036.8	256,871	256,992.5	258,054	258,429.1	258,787	259,829.7	257,076	257,313.1	260,582	261,419.4	265,955	266,516.1
XL-n3194-k161	**148,728**	**148,905.3**	148,994	149,161.6	148,937	149,064.9	149,949	150,141.2	149,803	150,105.8	149,391	149,684.6	156,795	158,561.8	163,628	171,798.3
XL-n3241-k115	**221,370**	**221,468.2**	221,637	221,732.6	221,574	221,678.8	222,319	222,510.0	223,357	223,872.1	221,870	222,017.7	223,914	224,294.5	227,918	230,547.8
XL-n3287-k30	**40,229**	**40,264.9**	40,235	40,273.4	40,230	40,285.7	40,735	41,009.4	40,887	41,092.5	40,538	40,974.3	40,883	41,244.8	44,225	45,338.0
XL-n3334-k934	**1,452,698**	**1,452,950.7**	1,453,358	1,453,639.3	1,453,205	1,453,531.7	1,456,863	1,457,777.2	1,465,703	1,466,924.1	1,453,276	1,453,614.9	1,468,960	1,473,610.6	1,477,435	1,480,074.3
XL-n3408-k524	**678,643**	**678,911.7**	679,979	680,284.2	679,812	680,047.4	683,312	683,727.2	685,634	686,864.6	680,287	680,759.4	786,005	800,425.6	748,231	778,465.2
XL-n3484-k436	**703,355**	**703,416.8**	703,402	703,459.9	703,387	703,454.9	703,924	704,063.7	704,451	704,902.8	703,617	703,735.5	704,495	704,700.1	706,947	707,320.0
XL-n3561-k229	**209,386**	**209,555.6**	209,797	209,977.3	209,693	209,832.3	211,438	211,715.0	211,379	212,076.8	210,098	210,344.3	224,490	232,075.0	224,338	233,124.7
XL-n3640-k211	**189,724**	**189,838.6**	189,992	190,110.6	189,877	190,038.0	191,105	191,291.3	191,146	191,531.6	190,218	190,427.7	194,899	196,261.0	199,577	200,624.1
XL-n3721-k77	**162,862**	**162,970.3**	163,221	163,468.7	163,041	163,241.5	164,231	164,631.6	166,563	167,084.5	164,077	164,447.5	167,294	168,623.0	176,024	177,188.8
XL-n3804-k29	**52,885**	**52,935.8**	52,979	53,054.8	52,948	53,026.2	53,468	53,958.4	53,176	53,306.6	53,269	53,429.2	53,676	54,224.7	60,096	61,880.2
XL-n3888-k1010	**1,880,368**	**1,882,369.0**	1,889,998	1,893,832.7	1,893,912	1,896,882.1	1,938,055	1,941,655.6	1,891,969	1,898,904.4	1,888,139	1,890,565.2	–	–	1,904,914	1,910,406.1
XL-n3975-k687	**525,901**	**526,048.1**	526,283	526,431.4	526,100	526,361.9	528,906	529,183.5	531,239	532,949.1	526,547	526,826.9	534,544	536,626.8	547,160	550,743.6
XL-n4063-k347	**548,931**	**549,115.2**	549,749	549,905.8	549,614	549,817.4	552,302	552,683.1	558,540	559,356.1	550,199	550,524.2	589,406	598,800.3	569,008	573,607.5
XL-n4153-k291	**356,034**	**356,149.2**	356,457	356,631.7	356,412	356,532.8	358,538	358,686.7	359,992	360,658.2	356,757	356,925.4	363,855	366,949.9	366,789	370,046.8
XL-n4245-k203	**229,659**	**229,743.2**	229,683	229,786.2	229,703	229,762.9	230,408	230,549.3	231,721	232,266.8	230,003	230,150.9	231,886	232,340.6	237,870	238,519.1
XL-n4340-k148	**244,226**	**244,431.7**	244,559	244,723.3	244,515	244,666.1	245,748	245,962.0	249,862	250,538.0	245,005	245,248.1	290,700	302,129.8	254,610	255,212.5
XL-n4436-k48	**61,477**	**61,583.1**	61,542	61,745.9	61,519	61,589.1	62,034	62,371.8	62,374	62,600.7	61,944	62,057.8	63,230	63,696.4	67,046	69,283.8
XL-n4535-k1134	**1,203,566**	**1,203,606.7**	1,203,574	1,203,619.9	1,203,605	1,203,655.5	1,204,133	1,204,297.9	1,204,967	1,205,208.8	1,203,971	1,204,074.4	1,204,631	1,204,811.8	1,206,068	1,206,309.5
XL-n4635-k790	**610,650**	**610,947.8**	611,371	611,617.3	611,191	611,437.2	615,225	615,774.5	621,541	622,572.0	612,062	612,478.8	–	–	636,983	643,476.9
XL-n4738-k487	**760,501**	**760,787.8**	761,734	762,019.3	761,570	761,880.7	765,520	765,816.6	772,923	774,216.4	762,244	762,728.4	848,584	876,646.7	786,677	792,775.0
XL-n4844-k321	**404,652**	**404,837.3**	406,051	406,484.1	405,610	405,876.3	407,136	407,539.3	410,938	411,848.0	405,738	406,164.6	410,413	410,799.4	433,448	437,853.2
XL-n4951-k203	**285,269**	**285,390.1**	285,493	285,668.7	285,387	285,575.4	286,866	287,171.6	292,698	293,247.8	286,085	286,311.6	301,081	306,062.4	295,805	296,654.3
XL-n5061-k184	**161,629**	**161,716.7**	161,878	162,125.9	161,799	162,041.9	162,767	162,910.9	163,647	164,240.8	162,248	162,458.5	168,384	169,806.0	169,156	170,004.9
XL-n5174-k55	**61,382**	61,491.6	61,439	61,554.6	61,388	**61,489.1**	62,696	63,190.9	62,838	63,365.1	62,301	62,655.7	66,940	67,775.3	71,694	74,070.0
XL-n5288-k1246	**1,960,101**	**1,960,957.8**	1,969,468	1,970,919.4	1,968,626	1,969,625.1	1,973,897	1,975,364.3	1,979,986	1,981,046.6	1,963,284	1,964,548.0	–	–	2,043,934	2,050,699.2
XL-n5406-k783	**1,040,536**	**1,040,723.8**	1,041,085	1,041,275.2	1,040,982	1,041,163.0	1,044,393	1,044,993.9	1,054,157	1,055,362.0	1,041,404	1,041,638.4	1,048,001	1,050,772.4	1,062,904	1,065,357.7
XL-n5526-k553	**336,898**	**336,984.8**	336,956	337,021.3	336,919	336,985.4	337,665	337,811.6	339,042	339,395.9	337,486	337,581.3	338,592	338,780.5	342,031	342,645.5
XL-n5649-k401	**644,866**	**644,987.8**	647,193	647,619.6	646,145	646,598.9	648,133	648,683.5	658,001	658,983.1	646,351	646,822.3	651,205	656,972.6	677,774	682,592.0
XL-n5774-k290	**250,207**	**250,337.8**	250,720	250,956.9	250,620	250,790.3	252,642	252,860.3	255,156	256,107.7	251,586	251,849.3	271,379	287,487.9	270,908	279,218.2
XL-n5902-k122	**217,447**	217,689.0	217,570	217,746.8	217,509	**217,668.5**	219,624	220,043.0	224,048	225,156.7	218,869	219,210.6	226,131	226,896.2	233,033	235,501.0
XL-n6034-k61	64,453	64,676.8	64,543	64,670.2	**64,448**	**64,615.0**	65,997	66,395.5	66,401	66,794.3	65,402	65,598.7	71,546	72,606.4	73,530	74,714.1
XL-n6168-k1922	**1,530,010**	**1,530,476.6**	1,533,690	1,534,292.6	1,532,722	1,533,331.4	1,539,812	1,540,593.5	1,551,851	1,553,139.1	1,533,332	1,534,231.8	–	–	1,572,323	1,576,529.3
XL-n6305-k1042	**1,177,528**	**1,177,837.0**	1,180,530	1,181,253.3	1,180,312	1,180,818.4	1,187,702	1,188,996.8	1,193,663	1,194,922.5	1,180,201	1,181,326.7	–	–	1,225,822	1,230,959.2
XL-n6445-k628	**996,623**	**996,804.7**	997,809	998,072.3	997,460	997,804.3	1,000,779	1,001,095.2	1,010,992	1,012,009.6	998,149	998,517.3	1,071,180	1,083,306.7	1,021,394	1,022,544.1
XL-n6588-k473	**334,068**	**334,232.1**	334,506	334,676.5	334,486	334,604.8	336,655	336,845.9	341,531	342,341.7	335,111	335,287.1	338,623	339,106.0	348,818	351,373.2
XL-n6734-k330	**448,031**	**448,257.5**	448,666	448,799.9	448,503	448,662.3	450,438	450,722.9	456,666	457,623.0	449,414	449,746.2	585,492	602,752.8	461,789	462,933.5
XL-n6884-k148	**181,809**	**181,960.4**	182,219	182,480.7	182,092	182,261.4	183,519	183,906.9	187,702	188,623.6	183,507	183,998.0	188,731	189,353.5	194,144	196,806.5
XL-n7037-k38	**70,845**	**70,906.9**	70,975	71,068.8	70,949	71,027.6	75,357	76,547.6	72,980	73,989.1	71,624	72,054.5	74,435	75,432.4	84,412	86,527.1
XL-n7193-k1683	**2,958,979**	**2,959,237.4**	2,965,043	2,966,154.3	2,963,460	2,964,390.1	2,973,722	2,976,353.2	2,978,019	2,978,644.7	2,961,569	2,962,056.3	–	–	3,073,256	3,082,216.0
XL-n7353-k1471	**1,537,811**	**1,537,904.2**	1,537,888	1,537,976.5	1,537,841	1,537,960.6	1,539,199	1,539,452.9	1,542,188	1,542,584.5	1,538,778	1,538,934.8	1,540,585	1,540,726.1	1,543,630	1,544,214.8
XL-n7516-k859	**573,902**	**574,104.2**	574,830	575,005.8	574,760	575,009.6	578,342	578,784.8	585,696	586,421.2	575,733	576,046.8	741,224	753,817.4	595,065	601,789.4
XL-n7683-k602	**702,098**	**702,303.9**	703,019	703,265.8	702,829	703,037.4	705,500	705,940.7	713,716	714,634.3	703,893	704,206.8	–	–	721,032	722,359.7
XL-n7854-k365	**659,221**	**659,311.3**	660,022	660,167.4	659,594	659,756.2	660,967	661,426.5	667,319	668,075.3	660,902	661,220.6	663,822	664,183.7	670,889	672,306.7
XL-n8028-k294	**266,900**	**267,065.9**	267,322	267,493.1	267,058	267,259.8	269,230	269,533.1	273,319	273,864.5	268,989	269,340.9	303,795	314,769.4	304,826	326,514.1

Continued on next page

Instance	Large-scale methods								Standard-scale methods							
	AILS-II		FILO		FILO2		KGLS$^{\mathrm{XXL}}$		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
XL-n8207-k108	**118,274**	118,509.0	118,531	118,710.4	118,392	**118,495.5**	119,872	120,368.0	122,006	122,311.5	119,737	120,013.0	125,375	126,054.1	129,611	130,632.8
XL-n8389-k2028	**3,358,731**	**3,359,593.2**	3,368,875	3,369,886.8	3,365,882	3,366,587.9	3,379,011	3,384,122.1	3,407,551	3,409,508.7	3,365,665	3,367,143.4	–	–	3,416,160	3,424,086.4
XL-n8575-k1297	**1,089,137**	**1,089,360.7**	1,089,976	1,090,163.5	1,089,681	1,089,920.0	1,094,516	1,094,951.1	1,108,196	1,109,688.1	1,090,800	1,091,190.2	1,111,459	1,122,709.8	1,124,655	1,129,545.4
XL-n8766-k1032	**906,406**	**906,592.3**	907,662	908,041.4	907,388	907,754.7	911,293	911,712.8	920,113	921,125.5	909,024	909,382.8	1,316,029	1,356,752.8	935,015	936,239.4
XL-n8960-k634	**773,383**	**773,515.7**	774,297	774,478.0	774,049	774,194.6	776,494	776,749.0	786,928	787,574.8	774,851	775,165.8	837,252	851,958.9	790,145	791,178.6
XL-n9160-k379	**324,092**	**324,277.1**	325,636	325,988.6	324,890	325,121.9	327,355	327,773.4	331,258	332,458.5	327,057	327,894.9	335,459	335,886.5	355,749	361,374.4
XL-n9363-k209	205,713	205,842.2	205,675	205,788.7	**205,575**	**205,690.5**	207,211	207,627.8	210,150	210,705.5	206,463	206,807.3	212,085	212,825.4	219,457	220,835.1
XL-n9571-k55	106,956	107,277.8	106,973	107,247.1	**106,791**	**106,987.1**	114,806	116,005.7	113,551	114,621.1	109,465	110,061.8	119,664	121,011.0	126,909	130,501.0
XL-n9784-k2774	**4,078,217**	**4,078,505.8**	4,080,198	4,080,925.8	4,078,841	4,079,247.6	4,088,203	4,091,318.6	4,108,083	4,109,693.8	4,080,493	4,081,111.9	–	–	4,113,609	4,119,287.6
XL-n10001-k1570	**2,333,757**	**2,334,348.4**	2,340,824	2,341,299.5	2,339,475	2,340,196.9	2,349,676	2,351,638.2	2,360,414	2,361,177.1	2,337,987	2,339,332.4	–	–	2,411,189	2,415,750.7
Avg. gap (%)	0.00	0.07	0.15	0.25	0.12	0.21	0.79	1.00	1.11	1.36	0.34	0.50	5.47	6.66	5.54	6.81
Avg. gap (%) $n < 3,400$	0.00	0.08	0.14	0.25	0.12	0.23	0.58	0.81	0.54	0.78	0.24	0.43	3.96	4.95	5.37	6.71
Avg. gap (%) $n > 3,400$	0.00	0.07	0.17	0.24	0.12	0.18	1.00	1.20	1.69	1.95	0.44	0.56	7.36	8.79	5.71	6.91

Note: LKH-3 was unable to find feasible solutions for 10 instances and found fewer than 60 feasible solutions for other 10 instances.

5 Additional Experimental Analyses

Moreover, having conducted extensive experiments on the XL instances reported in Table 2, we decided to exploit the fact that we had gathered all those different code implementations on a single platform to provide an updated performance snapshot of the reviewed methods across the wider range of available instances, including the X and XML instances. Table 3 therefore contains the results of 50 runs with a 10-minute limit. The computed average gaps are based on the BKSs available in CVRPLib. We also present separate average results for the 50 instances with fewer than 330 customers and for the 50 instances with more customers. Table 4 presents experiments with 10 runs of each instance of the XML set with a 1-minute limit. As there are too many instances (10,000), only aggregated gaps (averaged per instance attribute value and overall) with respect to the optima are shown.

Table 3: Results on X instances: 50 independent runs per instance with a 10-minute time limit. Best results are shown in **bold** and second-best results are underlined.

Instance	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
X-n101-k25	**27,591**	**27,591.0**	**27,591**	**27,591.0**	**27,591**	**27,591.0**	**27,591**	27,593.0	**27,591**	**27,591.0**	**27,591**	**27,591.0**	29,473	30,679.7	27,732	27,971.5
X-n106-k14	**26,362**	**26,362.0**	**26,362**	26,365.2	**26,362**	26,362.2	26,373	26,400.4	**26,362**	26,373.8	**26,362**	26,379.8	**26,362**	26,391.5	26,672	26,796.2
X-n110-k13	**14,971**	**14,971.0**	**14,971**	**14,971.0**	**14,971**	**14,971.0**	**14,971**	**14,971.0**	**14,971**	**14,971.0**	**14,971**	**14,971.0**	**14,971**	15,006.5	14,972	15,078.1
X-n115-k10	**12,747**	**12,747.0**	**12,747**	**12,747.0**	**12,747**	**12,747.0**	**12,747**	**12,747.0**	**12,747**	**12,747.0**	**12,747**	**12,747.0**	**12,747**	12,747.4	12,757	12,838.3
X-n120-k6	**13,332**	**13,332.0**	**13,332**	**13,332.0**	**13,332**	**13,332.0**	**13,332**	**13,332.0**	**13,332**	**13,332.0**	**13,332**	**13,332.0**	**13,332**	13,335.2	13,429	13,527.7
X-n125-k30	**55,539**	**55,539.0**	**55,539**	55,615.8	**55,539**	55,578.1	55,546	55,587.9	**55,539**	**55,539.0**	**55,539**	55,551.1	55,546	55,741.1	56,361	56,742.7
X-n129-k18	**28,940**	28,940.4	**28,940**	28,948.5	**28,940**	28,947.4	28,948	28,961.5	**28,940**	**28,940.0**	**28,940**	28,945.4	**28,940**	29,022.7	29,620	29,703.4
X-n134-k13	**10,916**	**10,916.0**	**10,916**	10,922.1	**10,916**	10,917.4	**10,916**	10,929.6	**10,916**	**10,916.0**	**10,916**	10,936.9	**10,916**	10,972.8	11,046	11,150.2
X-n139-k10	**13,590**	**13,590.0**	**13,590**	**13,590.0**	**13,590**	**13,590.0**	**13,590**	**13,590.0**	**13,590**	**13,590.0**	**13,590**	13,591.4	**13,590**	13,616.4	13,606	13,675.6
X-n143-k7	**15,700**	15,703.2	**15,700**	15,722.0	**15,700**	15,713.8	15,726	15,732.4	**15,700**	**15,700.0**	**15,700**	15,703.5	**15,700**	15,755.5	15,928	16,051.1
X-n148-k46	**43,448**	**43,448.0**	**43,448**	43,457.8	**43,448**	**43,448.0**	43,449	43,517.8	**43,448**	**43,448.0**	**43,448**	43,458.0	43,499	43,597.7	43,874	44,199.0
X-n153-k22	**21,220**	**21,224.5**	21,225	21,227.9	21,225	21,225.1	21,357	21,378.2	21,223	21,224.9	21,223	21,228.1	21,418	21,490.5	21,488	21,615.8
X-n157-k13	**16,876**	**16,876.0**	**16,876**	**16,876.0**	**16,876**	**16,876.0**	**16,876**	16,876.3	**16,876**	**16,876.0**	**16,876**	16,876.1	**16,876**	16,879.9	16,982	17,057.3
X-n162-k11	**14,138**	**14,138.0**	**14,138**	14,152.2	**14,138**	14,141.0	14,146	14,147.8	**14,138**	**14,138.0**	**14,138**	14,148.4	**14,138**	14,161.4	14,214	14,257.0
X-n167-k10	**20,557**	20,557.3	**20,557**	**20,557.0**	**20,557**	20,557.1	**20,557**	20,588.3	**20,557**	**20,557.0**	**20,557**	20,557.8	**20,557**	20,603.3	21,165	21,268.9
X-n172-k51	**45,607**	45,607.8	**45,607**	**45,607.0**	**45,607**	**45,607.0**	45,727	45,766.1	**45,607**	**45,607.0**	**45,607**	45,614.3	46,580	46,952.9	46,350	46,538.7
X-n176-k26	**47,812**	**47,812.0**	**47,812**	47,889.5	**47,812**	47,847.2	47,836	47,949.2	**47,812**	**47,812.0**	**47,812**	47,837.5	47,816	48,037.3	49,056	49,250.8
X-n181-k23	**25,569**	25,570.5	**25,569**	25,569.3	**25,569**	25,569.1	25,582	25,606.8	**25,569**	**25,569.0**	**25,569**	25,576.5	25,571	25,603.5	25,770	25,885.3
X-n186-k15	**24,145**	24,149.4	**24,145**	24,153.4	**24,145**	24,149.6	24,149	24,185.6	**24,145**	**24,145.0**	24,149	24,174.9	24,149	24,307.1	24,868	25,023.0
X-n190-k8	**16,980**	**16,980.6**	**16,980**	16,983.3	**16,980**	16,982.3	17,020	17,059.7	**16,980**	16,984.1	**16,980**	16,987.6	16,992	17,035.8	17,342	17,412.8
X-n195-k51	**44,225**	44,256.5	**44,225**	44,259.9	**44,225**	44,254.2	44,270	44,391.7	**44,225**	**44,225.0**	**44,225**	44,277.3	46,609	47,560.5	45,039	45,370.6
X-n200-k36	**58,578**	58,587.8	58,619	58,801.6	**58,578**	58,745.7	58,653	58,760.4	**58,578**	**58,578.0**	**58,578**	58,635.6	58,657	58,909.8	59,745	60,338.8
X-n204-k19	**19,565**	19,565.7	**19,565**	19,566.3	**19,565**	**19,565.0**	19,575	19,602.8	**19,565**	**19,565.0**	**19,565**	19,671.5	19,579	19,723.4	19,960	20,172.7
X-n209-k16	**30,656**	30,663.2	**30,656**	30,673.1	**30,656**	30,669.0	30,676	30,710.6	**30,656**	**30,656.0**	**30,656**	30,666.6	30,679	30,862.3	31,681	31,874.7
X-n214-k11	10,859	10,869.1	10,860	10,875.4	10,861	10,873.7	10,908	10,946.6	**10,856**	**10,859.3**	10,870	10,900.6	10,926	11,094.0	11,177	11,310.7
X-n219-k73	**117,595**	**117,595.0**	**117,595**	**117,595.0**	**117,595**	**117,595.0**	**117,595**	117,611.7	**117,595**	117,595.2	**117,595**	117,634.4	117,613	117,692.1	117,854	117,974.3
X-n223-k34	**40,437**	40,446.3	**40,437**	40,503.7	40,445	40,501.8	40,555	40,639.4	**40,437**	**40,437.2**	**40,437**	40,531.4	40,528	40,713.9	41,515	41,886.5
X-n228-k23	**25,742**	25,750.6	25,743	25,779.9	25,743	25,777.5	25,764	25,816.6	**25,742**	**25,742.5**	25,743	25,787.5	25,757	25,837.5	26,279	26,510.3
X-n233-k16	**19,230**	19,256.2	**19,230**	19,286.4	19,243	19,268.5	19,266	19,338.1	**19,230**	**19,230.0**	**19,230**	19,279.0	19,874	20,218.2	19,696	19,895.7
X-n237-k14	**27,042**	27,048.5	**27,042**	27,046.4	**27,042**	27,043.8	27,044	27,105.0	**27,042**	**27,042.0**	27,044	27,089.0	27,051	27,162.6	27,583	27,867.0
X-n242-k48	**82,751**	82,808.7	82,784	82,877.3	82,754	82,856.7	82,911	83,051.9	**82,751**	**82,801.3**	**82,751**	82,888.1	82,979	83,291.5	85,095	85,515.7

Continued on next page

Instance	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
X-n247-k50	**37,274**	**37,274.1**	**37,274**	37,444.6	**37,274**	37,423.1	37,303	37,371.2	**37,274**	37,279.8	37,305	37,372.4	37,409	37,528.1	37,819	38,212.9
X-n251-k28	**38,684**	38,722.1	38,687	38,777.9	38,689	38,770.1	38,734	38,795.6	**38,684**	**38,688.1**	38,687	38,817.1	38,842	38,970.5	39,704	39,998.7
X-n256-k16	**18,839**	18,871.8	18,880	18,880.0	18,880	18,880.0	18,880	18,888.7	**18,839**	**18,839.9**	18,880	18,889.2	18,931	19,070.7	19,034	19,223.9
X-n261-k13	**26,558**	26,574.4	26,561	26,646.6	26,561	26,624.1	26,657	26,695.3	**26,558**	**26,561.4**	**26,558**	26,638.7	26,691	26,879.5	27,518	27,850.6
X-n266-k58	**75,478**	**75,540.9**	75,529	75,774.0	75,516	75,731.0	75,667	75,768.5	**75,478**	75,597.5	75,498	75,622.3	75,792	76,077.8	77,410	77,871.4
X-n270-k35	35,303	35,329.4	35,309	35,349.2	35,309	35,337.6	35,376	35,419.0	**35,291**	**35,302.4**	35,323	35,367.5	36,081	36,628.6	36,208	36,600.6
X-n275-k28	**21,245**	21,247.5	**21,245**	21,248.6	**21,245**	21,245.4	**21,245**	21,315.1	**21,245**	**21,245.0**	**21,245**	21,294.5	**21,245**	21,304.9	21,858	22,035.6
X-n280-k17	33,505	33,563.4	33,531	33,624.4	33,524	33,592.1	33,593	33,665.3	**33,503**	**33,545.0**	33,526	33,616.8	33,692	34,042.8	34,302	34,949.7
X-n284-k15	**20,215**	20,261.7	20,226	20,266.2	20,241	20,262.8	20,291	20,348.9	20,216	**20,242.4**	20,250	20,296.5	20,350	20,506.4	20,815	21,074.8
X-n289-k60	**95,151**	**95,263.0**	95,333	95,540.7	95,333	95,528.0	95,518	95,647.5	95,196	95,284.8	95,259	95,373.0	97,591	99,190.4	97,784	98,266.9
X-n294-k50	47,169	47,209.6	47,225	47,273.5	47,180	47,259.3	47,319	47,416.2	**47,161**	**47,188.0**	47,187	47,288.7	47,515	47,996.5	48,651	49,243.0
X-n298-k31	**34,231**	34,259.8	34,234	34,290.2	**34,231**	34,280.0	34,306	34,377.3	**34,231**	**34,233.6**	34,233	34,273.5	34,234	34,633.3	35,835	36,513.7
X-n303-k21	**21,736**	21,762.3	21,760	21,805.4	21,754	21,800.9	21,840	21,904.5	21,738	**21,746.1**	21,747	21,777.2	21,852	21,945.4	22,164	22,492.2
X-n308-k13	**25,859**	25,878.9	25,869	25,984.5	25,862	25,925.0	25,973	26,077.6	25,861	**25,872.6**	25,883	26,183.1	26,017	26,217.4	26,648	27,111.0
X-n313-k71	**94,044**	**94,094.2**	94,214	94,334.6	94,212	94,330.8	94,410	94,667.7	**94,044**	94,103.5	94,084	94,224.1	95,640	96,831.8	96,377	96,965.1
X-n317-k53	**78,355**	**78,356.3**	**78,355**	78,356.9	**78,355**	78,357.3	78,368	78,392.7	**78,355**	78,357.0	78,358	78,391.6	78,405	78,449.5	78,831	79,260.9
X-n322-k28	29,854	29,866.5	29,848	29,934.7	29,854	29,922.9	29,878	29,992.1	**29,834**	**29,848.2**	29,863	29,919.0	29,972	30,232.6	31,053	31,353.5
X-n327-k20	**27,532**	27,586.1	27,556	27,619.9	27,549	27,605.5	27,604	27,641.6	**27,532**	**27,547.3**	27,597	27,640.0	27,728	27,919.7	28,470	28,816.6
X-n331-k15	31,103	31,104.2	31,103	**31,103.4**	31,103	31,103.9	31,105	31,176.0	**31,102**	31,103.8	31,114	31,129.7	31,199	31,424.0	32,267	32,603.3
X-n336-k84	**139,139**	**139,277.6**	139,292	139,592.7	139,237	139,517.1	139,838	140,073.1	139,209	139,309.7	139,189	139,347.8	143,180	144,751.1	142,104	143,176.2
X-n344-k43	42,056	42,103.2	42,083	42,210.6	42,068	42,177.0	42,156	42,259.3	**42,055**	**42,073.7**	42,079	42,160.1	42,358	42,561.8	43,677	44,038.1
X-n351-k40	**25,900**	25,955.9	25,955	26,005.9	25,935	26,003.6	26,073	26,149.6	25,932	**25,948.1**	25,955	25,999.0	26,171	26,453.8	27,071	27,417.4
X-n359-k29	**51,505**	**51,552.7**	51,514	51,628.2	51,509	51,609.3	51,709	51,871.0	51,516	51,633.8	51,507	51,576.4	51,760	51,980.4	53,594	54,125.5
X-n367-k17	**22,814**	22,824.4	**22,814**	22,820.7	**22,814**	22,820.0	22,842	23,026.5	**22,814**	**22,814.0**	**22,814**	22,837.1	22,903	23,070.0	23,416	23,791.4
X-n376-k94	**147,713**	**147,715.1**	**147,713**	147,724.7	**147,713**	147,721.7	147,732	147,778.9	**147,713**	147,715.9	147,736	147,808.0	147,807	147,960.5	148,544	148,719.2
X-n384-k52	65,966	**66,041.3**	65,974	66,111.1	65,980	66,091.3	66,133	66,298.9	**65,953**	66,059.9	65,978	66,145.5	66,811	67,427.2	68,292	68,927.4
X-n393-k38	**38,260**	38,286.4	38,285	38,309.3	38,263	38,296.8	38,353	38,427.8	**38,260**	**38,260.5**	38,341	38,416.0	38,422	38,601.8	40,062	40,636.2
X-n401-k29	**66,201**	**66,222.4**	66,211	66,272.1	66,222	66,253.1	66,366	66,439.9	66,203	66,244.7	66,202	66,266.7	66,448	66,599.6	67,812	68,210.6
X-n411-k19	**19,712**	19,740.0	19,742	19,781.1	19,756	19,775.5	19,780	19,937.0	**19,712**	**19,721.5**	19,731	19,781.9	19,848	20,079.3	20,445	20,830.3
X-n420-k130	**107,798**	**107,835.8**	107,810	107,927.0	107,826	107,931.6	107,886	108,164.6	**107,798**	107,842.4	107,801	107,899.4	108,135	108,461.8	110,604	111,741.4
X-n429-k61	**65,455**	65,520.4	65,505	65,594.4	65,482	65,579.9	65,549	65,719.7	65,465	**65,500.0**	65,487	65,627.7	65,986	66,345.5	68,189	68,721.2
X-n439-k37	**36,395**	36,407.0	**36,395**	36,400.4	**36,395**	**36,397.7**	36,402	36,464.9	**36,395**	36,398.0	36,402	36,486.0	36,464	36,633.5	37,374	37,704.0
X-n449-k29	**55,236**	**55,313.2**	55,296	55,438.0	55,310	55,391.7	55,614	55,774.3	55,277	55,405.2	55,282	55,443.2	55,898	56,319.5	58,235	59,031.5
X-n459-k26	24,141	24,172.5	24,141	24,201.7	24,143	24,187.3	24,228	24,287.4	**24,139**	**24,167.7**	24,180	24,245.2	24,366	24,589.0	25,441	25,728.5
X-n469-k138	**221,841**	**222,056.2**	222,479	223,228.5	222,638	223,138.9	222,254	222,652.3	221,999	222,210.2	222,013	222,323.5	227,105	228,711.1	228,877	230,597.2
X-n480-k70	**89,449**	**89,460.5**	89,476	89,624.7	89,466	89,607.5	89,667	89,805.8	89,470	89,543.5	89,465	89,593.2	89,871	90,168.3	92,556	92,977.3
X-n491-k59	**66,484**	**66,561.7**	66,550	66,711.7	66,585	66,675.7	66,880	67,040.8	66,531	66,663.2	66,552	66,702.9	67,099	67,619.1	69,843	70,877.9
X-n502-k39	**69,226**	**69,233.4**	69,227	69,250.8	69,227	69,254.0	69,239	69,291.2	69,232	69,255.6	69,246	69,278.1	69,288	69,355.8	69,896	70,174.1
X-n513-k21	**24,201**	24,238.9	**24,201**	24,243.7	**24,201**	24,224.8	24,279	24,340.4	**24,201**	**24,201.9**	24,238	24,318.5	24,372	24,565.0	25,315	25,863.1
X-n524-k153	**154,603**	**154,625.3**	154,612	155,008.3	154,610	154,963.1	155,519	156,120.7	154,612	154,776.5	154,814	155,014.2	155,514	155,795.6	156,051	156,975.3
X-n536-k96	**94,853**	**94,944.8**	95,374	95,547.7	95,369	95,527.0	95,527	95,705.0	94,997	95,115.8	95,093	95,238.1	96,418	97,091.2	98,443	99,458.6
X-n548-k50	**86,700**	86,746.9	**86,700**	86,738.4	**86,700**	**86,735.7**	86,802	86,889.1	86,709	86,787.3	86,749	86,835.9	86,997	87,210.4	89,134	89,366.0
X-n561-k42	**42,719**	42,769.0	42,752	42,834.6	42,744	42,802.6	42,899	43,024.5	**42,719**	**42,754.3**	42,791	42,902.8	42,934	43,125.8	44,831	45,903.4
X-n573-k30	**50,722**	**50,745.1**	50,741	50,809.7	50,740	50,792.0	50,836	50,977.7	50,776	50,824.2	50,734	50,860.2	51,028	51,301.1	51,995	52,659.2
X-n586-k159	**190,316**	**190,410.3**	190,825	191,138.3	190,729	191,036.6	190,782	191,038.4	190,401	190,624.1	190,526	190,727.4	191,326	191,894.4	196,800	198,204.8
X-n599-k92	**108,487**	**108,601.8**	108,634	108,773.3	108,623	108,757.3	108,898	109,096.7	108,582	108,721.2	108,585	108,763.7	117,113	119,734.5	112,730	113,547.1
X-n613-k62	**59,536**	**59,618.8**	59,612	59,737.4	59,610	59,744.9	60,020	60,192.6	59,599	59,731.7	59,641	59,799.3	60,341	60,672.0	63,207	64,148.2
X-n627-k43	**62,178**	**62,226.5**	62,215	62,307.8	62,232	62,298.7	62,408	62,524.2	62,297	62,443.7	62,273	62,361.4	62,754	63,202.6	64,280	64,984.8

Continued on next page

Instance	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
X-n641-k35	**63,705**	**63,785.1**	63,754	63,852.0	63,747	63,838.0	63,941	64,109.9	63,782	63,924.1	63,799	63,909.2	64,455	64,761.0	66,305	66,836.5
X-n655-k131	**106,780**	**106,795.0**	**106,780**	106,812.2	**106,780**	106,805.7	106,870	106,921.5	106,802	106,820.8	106,817	106,871.9	106,917	107,050.4	107,626	107,817.3
X-n670-k130	**146,421**	**146,830.4**	147,018	147,564.2	147,177	147,634.7	148,247	148,590.4	146,629	146,940.7	146,977	147,432.4	148,128	148,822.2	151,101	151,958.1
X-n685-k75	**68,228**	**68,317.3**	68,336	68,514.6	68,340	68,484.9	68,692	68,904.4	68,316	68,427.2	68,297	68,447.9	69,089	69,532.2	72,860	74,239.4
X-n701-k44	**81,938**	**82,021.5**	81,980	82,145.8	81,949	82,056.7	82,324	82,525.3	82,170	82,335.6	82,008	82,162.1	82,715	83,051.6	86,126	87,264.0
X-n716-k35	**43,364**	**43,408.4**	43,462	43,534.3	43,436	43,501.8	43,695	43,787.1	43,450	43,547.1	43,477	43,553.0	44,018	44,191.0	45,580	46,431.9
X-n733-k159	**136,212**	**136,315.1**	136,320	136,461.2	136,241	136,446.9	136,747	136,931.7	136,336	136,482.4	136,272	136,462.9	137,138	137,753.0	141,537	144,049.3
X-n749-k98	**77,326**	**77,447.7**	77,509	77,640.3	77,484	77,600.8	77,998	78,140.6	77,594	77,755.7	77,456	77,658.4	78,593	79,048.9	81,629	83,038.2
X-n766-k71	**114,430**	**114,497.5**	114,713	114,960.8	114,651	114,881.9	115,019	115,344.6	114,657	114,792.1	114,666	114,861.6	115,634	116,303.9	120,732	124,000.6
X-n783-k48	**72,415**	**72,512.5**	72,475	72,632.2	72,472	72,581.3	72,906	73,110.1	72,742	72,964.5	72,529	72,715.7	73,272	73,688.5	76,954	77,799.9
X-n801-k40	**73,309**	**73,384.5**	73,331	73,412.1	73,316	73,404.3	73,531	73,681.3	73,409	73,599.4	73,381	73,479.0	73,888	74,105.8	75,787	76,433.4
X-n819-k171	**158,204**	**158,291.5**	158,695	158,994.2	158,717	158,954.1	159,012	159,217.8	158,360	158,598.0	158,443	158,656.8	162,463	164,629.7	164,214	165,168.7
X-n837-k142	**193,784**	**193,865.2**	194,111	194,351.2	194,097	194,300.5	194,437	194,702.0	194,205	194,635.2	193,941	194,154.2	195,473	195,970.7	200,297	201,520.6
X-n856-k95	**88,966**	**89,027.2**	88,975	89,043.9	88,990	89,046.4	89,155	89,260.9	88,985	89,054.0	89,060	89,191.7	89,287	89,539.4	90,949	91,477.5
X-n876-k59	**99,370**	**99,452.1**	99,481	99,579.4	99,392	99,537.5	99,927	100,074.5	99,673	99,929.3	99,493	99,640.4	100,448	100,713.8	102,926	103,825.4
X-n895-k37	**53,882**	**53,997.8**	53,979	54,073.1	53,900	54,045.4	54,170	54,374.3	54,008	54,189.6	54,038	54,206.1	56,279	57,228.5	57,333	58,373.7
X-n916-k207	**329,209**	**329,368.1**	330,001	330,514.9	329,916	330,467.6	330,285	330,564.4	330,505	331,092.1	329,491	329,769.2	331,845	332,602.2	339,940	342,160.2
X-n936-k151	**132,930**	**133,023.1**	133,119	133,520.1	133,074	133,363.6	133,423	133,660.7	133,139	133,545.5	133,018	133,538.2	140,139	141,689.8	139,363	141,762.2
X-n957-k87	85,475	**85,527.4**	**85,472**	85,547.9	85,478	85,535.9	85,692	85,779.6	85,506	85,591.1	85,601	85,696.0	85,945	86,202.0	88,222	88,623.4
X-n979-k58	**118,971**	**119,031.7**	119,139	119,272.0	119,066	119,174.6	119,422	119,726.8	119,588	119,828.4	119,133	119,256.0	119,997	121,235.2	122,996	124,024.9
X-n1001-k43	**72,380**	**72,486.5**	72,471	72,592.0	72,430	72,540.6	72,974	73,181.6	72,688	73,039.7	72,426	72,683.7	73,725	74,230.3	77,564	78,500.8
Avg. gap (%)	0.01	0.08	0.08	0.22	0.07	0.19	0.29	0.48	0.07	0.15	0.08	0.24	0.96	1.61	2.96	3.95
Avg. gap (%) ($n < 330$)	0.00	0.05	0.03	0.14	0.03	0.11	0.15	0.31	0.00	0.02	0.03	0.17	0.67	1.34	2.04	2.89
Avg. gap (%) ($n > 330$)	0.02	0.11	0.13	0.30	0.12	0.26	0.43	0.66	0.13	0.28	0.13	0.31	1.25	1.87	3.87	5.01

Note: LKH-3 found only 47 feasible solutions for the instance X-n670-k30.

Table 4: Results on XML100 instances: 10 independent runs per instance with a one-minute time limit. Entries report the average optimality gap (%) for each subgroup of instances defined by an attribute value or level.

Attribute	Level	AILS-II		FILO		FILO2		KGLS^{XXL}		HGS-CVRP		SISRs		LKH-3		OR-Tools	
		Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean	Best	Mean
Depot pos.	R	0.002	0.008	0.016	0.050	0.013	0.038	0.075	0.150	**0.001**	**0.002**	0.014	0.064	0.273	0.506	1.047	1.496
	C	0.004	0.009	0.009	0.032	0.006	0.025	0.043	0.096	**0.001**	**0.001**	0.016	0.060	0.323	0.550	0.695	1.099
	E	**0.002**	0.010	0.028	0.075	0.023	0.060	0.117	0.227	0.003	**0.006**	0.025	0.084	0.151	0.379	1.280	1.766
Customer pos.	R	0.003	0.011	0.011	0.048	0.010	0.036	0.048	0.119	**0.000**	**0.002**	0.013	0.059	0.298	0.577	1.150	1.557
	C	**0.002**	0.007	0.027	0.057	0.021	0.047	0.126	0.219	0.003	**0.006**	0.025	0.077	0.183	0.345	0.840	1.301
	RC	0.002	0.010	0.015	0.051	0.011	0.040	0.061	0.135	**0.001**	**0.002**	0.017	0.072	0.268	0.514	1.028	1.498
Demand dist.	U	0.000	0.001	0.000	0.004	0.000	0.003	0.006	0.026	**0.000**	**0.000**	0.008	0.030	0.010	0.089	0.632	0.940
	1–10	0.001	0.008	0.006	0.040	0.005	0.029	0.051	0.126	**0.001**	**0.003**	0.012	0.061	0.085	0.285	1.162	1.617
	5–10	0.001	0.006	0.014	0.047	0.012	0.034	0.031	0.091	**0.000**	**0.001**	0.014	0.066	0.103	0.304	1.108	1.550
	1–100	0.003	0.014	0.027	0.080	0.022	0.064	0.088	0.179	**0.003**	**0.006**	0.023	0.072	0.325	0.648	1.185	1.672
	50–100	0.005	0.014	0.033	0.072	0.025	0.057	0.068	0.131	**0.000**	**0.002**	0.024	0.089	0.345	0.650	1.152	1.596
	Q	0.003	0.012	0.031	0.076	0.026	0.062	0.086	0.175	**0.001**	**0.004**	0.019	0.071	0.484	0.804	1.141	1.632
	SL	**0.004**	0.010	0.012	0.046	0.009	0.038	0.216	0.376	0.005	**0.008**	0.028	0.095	0.441	0.602	0.666	1.162
Route size r	VS	0.008	0.019	0.050	0.111	0.042	0.096	0.114	0.192	**0.004**	**0.006**	0.018	0.067	0.880	1.288	1.206	1.641
	S	0.003	0.014	0.032	0.084	0.026	0.068	0.126	0.225	**0.001**	**0.004**	0.024	0.079	0.454	0.802	1.415	1.963
	M	**0.001**	0.008	0.013	0.050	0.010	0.036	0.102	0.224	0.002	**0.004**	0.017	0.066	0.156	0.433	1.315	1.839
	L	**0.001**	0.007	0.007	0.030	0.004	0.020	0.052	0.136	0.001	**0.002**	0.012	0.052	0.079	0.290	1.087	1.572
	VL	0.001	0.005	0.002	0.021	0.001	0.013	0.037	0.109	**0.001**	**0.002**	0.012	0.049	0.025	0.159	0.749	1.158
	UL	**0.001**	**0.002**	0.001	0.016	0.002	0.014	0.036	0.057	0.001	0.002	0.027	0.102	0.004	0.033	0.266	0.541
Overall		0.002	0.009	0.018	0.052	0.014	0.041	0.078	0.158	**0.001**	**0.003**	0.018	0.069	0.250	0.479	1.006	1.452

6 Discussions and analyses

Results on the XL set. As seen in these experiments, most of the initial BKSs for the new XL instances were achieved by methods specifically designed and calibrated for large-scale problems. Notably, AILS-II achieved 93 out of the 100 initial BKS, followed by FILO2 (6 instances) and FILO (1 instance), therefore positioning itself as the leading method for solving large-scale VRPs as the start of the challenge. The average solution quality achieved by the different methods is consistent with this ranking: on the XL instances, AILS-II attains a mean gap of 0.07% relative to the initial BKSs, compared to 0.21% for FILO2, 0.25% for FILO, and 1.00% for KGLS-XXL.

Results on all instances. Our broader analysis across all instance dimensions also highlights several additional trends. On all subcategories of instances with 100 customers, as well as the first half of the X instances (with up to 330 customers), the classic HGS-CVRP achieves the best average solution quality consistently across all considered methods. In contrast, on the larger half of the X instances and on the XL set, AILS-II clearly outperforms the other approaches. The performance of SISR is also noteworthy, as it exhibits good scalability on the XL instances without parameter adaptation, while simultaneously achieving good results on the medium-scale instance sets. Overall, these initial results suggest a transition in effective solution methodologies as instance size increases: from population-based methods, such as HGS-CVRP, which focus heavily on diversification and concurrently evolve multiple solutions through crossover and local search on small and medium-scale instances, to methods that increasingly focus on the refinement of a single incumbent solution, such as SISR and, more prominently, AILS-II, in the larger-scale regime.

Limitations and perspectives. The present experiments adopted a rigid stance regarding parameter calibration (default values of all algorithms, regardless of the instance sizes for which they were originally designed), together with relatively tight computational limits relative to the size of the problems addressed on a single CPU thread. A tenfold increase in instance size is likely to induce different computational bottlenecks, and the current parameter settings and time limits do not allow, for example, convergence of HGS-CVRP on the XL set. A more complete picture of the performance of classic "medium-scale" CVRP algorithms on the XL set would therefore require some parameter calibration.

Additionally, rather than focusing on directly solving these large-scale instances, additional analyses should investigate the capabilities of those medium-scale solution methods *for the iterative refinement of a single incumbent solution* through the repeated solution of medium-scale subproblems. This is typical in (possibly parallel) decomposition techniques, and a very straightforward approach to capitalize on different search methodologies. This, along with information gained throughout the challenge, may help further understand whether single-trajectory solution improvement methods (e.g., ILS-based) should be preferred over population-based approaches in this larger-scale regime.

Acknowledgments

We thank Florian Arnold for recently making KGLS$^{\mathrm{XXL}}$ open source, which notably supported this project and enabled its use in our work and by others. We thank Arthur Ferraz and João Marcelo Soares for giving us access to their implementation of SISRs. The extensive experiments reported in this paper were conducted in machines provided by Calcul Québec and the Digital Research Alliance of Canada. This support is gratefully acknowledged.

References

[1] 12th DIMACS implementation challenge: Capacitated Vehicle Routing Problem (CVRP). `http://dimacs.rutgers.edu/programs/challenge/vrp/cvrp/`, 2022. Accessed: December 28, 2025.

[2] EURO Meets NeurIPS 2022 Vehicle Routing Competition. `https://euro-neurips-vrp-2022.challenges.ortec.com/`, 2023. Accessed: December 28, 2025.

[3] Luca Accorsi and Daniele Vigo. A fast and scalable heuristic for the solution of large-scale capacitated vehicle routing problems. *Transportation Science*, 55(4):832–856, 2021.

[4] Luca Accorsi and Daniele Vigo. Routing one million customers in a handful of minutes. *Computers & Operations Research*, 164:106562, 2024.

[5] Florian Arnold, Michel Gendreau, and Kenneth Sörensen. Efficiently solving very large-scale routing problems. *Computers & Operations Research*, 107:32–42, 2019. ISSN 0305-0548. doi: https://doi.org/10.1016/j.cor.2019.03.006.

[6] P. Augerat, J. Belenguer, E. Benavent, A. Corberán, D. Naddef, and G. Rinaldi. Computational results with a branch and cut code for the capacitated vehicle routing problem. Technical Report 949-M, Université Joseph Fourier, Grenoble, France, 1995.

[7] Jan Christiaens and Greet Vanden Berghe. Slack induction by string removals for vehicle routing problems. *Transportation Science*, 54(2):417–433, 2020.

[8] Nicos Christofides and Samuel Eilon. An algorithm for the vehicle-dispatching problem. *Journal of the Operational Research Society*, 20(3):309–318, 1969.

[9] Luciano Costa, Claudio Contardo, and Guy Desaulniers. Exact branch-price-and-cut algorithms for vehicle routing. *Transportation Science*, 53(4):946–985, 2019.

[10] George B Dantzig and John H Ramser. The truck dispatching problem. *Management science*, 6(1): 80–91, 1959.

[11] Arthur M. Ferraz and João Marcelo G. Soares. Implementation in C++ of slack induction by string removals for vehicle routing problems. Personal communication, 2025. Private source code repository shared directly by the authors.

[12] M. Fisher. Optimal solution of vehicle routing problem using minimum k-trees. *Operations Research*, 42:626–642, 1994.

[13] B. Golden, E. Wasil, J. Kelly, and I. Chao. The impact of metaheuristics on solving the vehicle routing problem: algorithms, problem sets, and computational results. In *Fleet management and logistics*, pages 33–56. Springer, 1998.

[14] André Hottung, Federico Berto, Chuanbo Hua, Nayeli Gast Zepeda, Daniel Wetzel, Michael Römer, Haoran Ye, Davide Zago, Michael Poli, Stefano Massaroli, Jinkyoo Park, and Kevin Tierney. VRPAgent: LLM-driven discovery of heuristic operators for vehicle routing problems. *arXiv preprint arXiv:2510.07073*, 2025.

[15] Vinícius R. Máximo, Jean-François Cordeau, and Mariá C. V. Nascimento. AILS-II: An Adaptive Iterated Local Search Heuristic for the Large-Scale Capacitated Vehicle Routing Problem. *INFORMS Journal on Computing*, 36(4):974–986, 2024. doi: 10.1287/ijoc.2023.0106.

[16] Diego Pecin, Artur Pessoa, Marcus Poggi, and Eduardo Uchoa. Improved branch-cut-and-price for capacitated vehicle routing. *Mathematical Programming Computation*, 9(1):61–100, 2017.

[17] Artur Pessoa, Ruslan Sadykov, Eduardo Uchoa, and François Vanderbeck. A generic exact solver for vehicle routing and related problems. *Mathematical Programming*, 183(1):483–523, 2020.

[18] Marcus Poggi and Eduardo Uchoa. New exact algorithms for the capacitated vehicle routing problem. In Paolo Toth and Daniele Vigo, editors, *Vehicle Routing: Problems, Methods, and Applications, Second Edition*, pages 59–86. SIAM, 2014.

[19] Eduardo Queiroga, Ruslan Sadykov, Eduardo Uchoa, and Thibaut Vidal. 10,000 optimal CVRP solutions for testing machine learning based heuristics. In *AAAI-22 workshop on machine learning for operations research (ML4OR)*, 2021.

[20] Yves Rochat and Éric D Taillard. Probabilistic diversification and intensification in local search for vehicle routing. *Journal of heuristics*, 1(1):147–167, 1995.

[21] João Marcos Pereira Silva, Eduardo Uchoa, and Anand Subramanian. Cluster branching for vehicle routing problems. *INFORMS Journal on Computing*, 2025.

[22] Eduardo Uchoa, Diego Pecin, Artur Pessoa, Marcus Poggi, Thibaut Vidal, and Anand Subramanian. New benchmark instances for the capacitated vehicle routing problem. *European Journal of Operational Research*, 257(3):845–858, 2017.

[23] Thibaut Vidal. Hybrid genetic search for the CVRP: Open-source implementation and SWAP* neighborhood. *Computers & Operations Research*, 140:105643, 2022.

[24] Zhengzhong You and Yu Yang. RouteOpt: An open-source modular exact solver for vehicle routing problems. *Available at SSRN 5314242*, 2025.