Benchmark Set for the IEEE WCCI-2020 Competition on Evolutionary Computation for the Electric Vehicle Routing Problem

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1 Introduction

Transportation has been the main contributor to CO_2 emissions. Due to global warming, pollution and climate changes, logistic companies such as FedEx, UPS, DHL and TNT have became more sensitive to the environment and they are investing in ways to reduce the CO_2 emissions that result as part of their daily operations. There is no doubt that using Electric Vehicles (EVs) instead of conventional vehicles will significantly contribute to the reduction of CO_2 emissions [1], fact that increases the interest of logistic companies in utilizing EVs for their daily operation.

In these circumstances, the problem of routing a fleet of EVs has emerged, namely the Electric Vehicle Routing Problem (EVRP) [2]. In this report, a benchmark set of the EVRP instances is provided with known and unknown optimum values. The rest of this report is organized as follows. Section 2 presents the EVRP problem in which a detailed mathematical formulation of the problem is presented. Section 3 gives details of the EVRP benchmark set while, Section 4 demonstrates the criteria of evaluating an algorithm on the benchmark set. Finally Section 5 concludes this report.

2 The Electric Vehicle Routing Problem

The EVRP is a challenging $\mathcal{NP}$-hard combinatorial optimization problem as it is an extension of the ordinary shorted path problem incorporating additional constraints [3]. The EVRP can be described as follows: given a fleet of EVs, we need to find the best possible routes within the battery charge level limits, starting and ending to the central depot, to serve a set of customers.

Usually, the problem is expressed with the use of a fully connected weighted graph $G = (V, A)$, where $V = \{0 \cup I \cup F'\}$ is a set of nodes and $A = \{(i, j) \mid i, j \in V, i \neq j\}$ is a set of arcs connecting these nodes. Moreover, 0, I and F' denote, the central depot, the set of customers, and the set of β_i node copies[1] of each charging station $i \in F$ (i.e., $|F'| = \sum_{i \in F} \beta_i$), respectively.

A fleet of homogeneous EVs is positioned at the depot with parameters C and Q representing the maximal carrying capacity and the maximal battery charging level of the EVs, respectively. With each arc, a non-negative value distance d_{ij} is associated which represents the euclidean distance between nodes i and j. Each traveled arc (i, j) consumes the amount hd_{ij} of the remaining battery charge level of the EV traveling the arc, where parameter h denotes the non-negative consumption rate of the EVs. Furthermore, each node $i \in V$ is assigned a positive demand q_i to each customer i, whereas $q_i = 0\, \forall i \notin I$. Variables u_i and y_i denote the remaining carrying capacity and remaining battery charge level of an EV on its arrival at node $i \in V$. All EVs are assumed to start fully loaded and charged from their depot (i.e., $u_0 = C$ and $y_0 = Q$). The objective of the EVRP problem is to serve all customers using the fleet of EVs by minimizing the total distance traveled considering that each EV has a limited battery charge level and limited carrying capacity.

Consequently, the EVRP can be mathematically formulated as follows:

$$\min \sum_{i \in V, j \in V, i \neq j} d_{ij} x_{ij}, \tag{1}$$

s.t

$$\sum_{j \in V} x_{ij} = 1,\ \forall i \in I, i \neq j, \tag{2}$$

$$\sum_{j \in V} x_{ij} - \sum_{j \in V} x_{ji} = 0, \forall i \in V, i \neq j, \tag{3}$$

$$u_j \leq u_i - q_i x_{ij} + C(1 - x_{ij}),\ \forall i \in V, \forall j \in V \backslash \{0\}, i \neq j, \tag{4}$$

$$0 \leq u_i \leq C,\ \forall i \in V, \tag{5}$$

[1] The node copies of stations are used to permit multiple visits to each charging station in a similar manner as proposed in [4]. An upper bound on the number of node copies to consider is $2|I|$, because at worst an EV for each customer is needed and a visit to a charging station before and after serving it [5].

$$y_j = \sum_{i \in V} x_{ij}(y_i - hd_{ij}), \forall j \in I, i \neq j, \quad (6)$$

$$y_i \geq hd_{ij}x_{ij}, \ \forall i \in V, \forall j \in V, i \neq j, \quad (7)$$

$$0 \leq y_i \leq Q, \ \forall i \in V, \quad (8)$$

$$x_{ij} \in \{0, 1\}, \ \forall i \in V, \ \forall j \in V, i \neq j, \quad (9)$$

where Eq. (1) defines the EVRP objective function, Eq. (2) enforce the connectivity of customer visits, with Eq. (3) establish flow conservation by guaranteeing that at each node, i.e., the number of incoming arcs is equal to the number of outgoing arcs. Eq. (4) and Eq. (5) guarantee demand fulfillment at all customers by assuring a non-negative cargo load upon arrival at any node including the depot, Eq. (6), Eq. (7) and Eq (8) ensure that the battery charge never falls below 0, and Eq. (9) define a set of binary decision variables which each one equal to 1 if an arc is traveled and 0 otherwise.

3 Description of EVRP Benchmark Set

The EVRP benchmark set consists of two groups of problems:

1. consists of 7 small problem instances (up to 100 customers) in which their upper bound values are provided.

2. consists of 10 larger problem instances (up to 1000 customers) in which their upper bound values are not provided.

The first group of EVRP instances was generated by extending the well-known instances of the conventional vehicle routing problem from Christofides and Eilon [6] (see Figure 1) while the second group is an extension of the recent instances of the conventional vehicle routing problem from Uchoa *et al.* [7] (see Figure 2). The instances of the first group are useful for testing (e.g., validation of the solver, parameter tuning, etc.), since the large problem instances are more challenging and time-consuming to solve. The details of all the generated EVRP instances are summarized in Table 1. The columns in Table 1 present the number of customers, the number of depots, the number of charging stations, the minimum number of routes, the maximum load of an EV, the maximum battery charge level of an EV, the energy consumption constant, and an upper bound value (it could be optimal in some cases but it is not verified yet).

The file of each EVRP instance of the benchmark set contains the following keywords:

- `COMMENT`: information about the problem instance

- `OPTIMAL_VALUE`: the optimal value (or upper bound) of the problem instance (if known; otherwise is set to 0)

Table 1: Details of the EVRP benchmark set

name	#customers	#depots	#stations	#routes	C	Q	h	UB
E-n22-k4.evrp	21	1	8	4	6000	94	1.2	384.67
E-n23-k3.evrp	22	1	9	3	4500	190	1.2	573.13
E-n30-k3.evrp	29	1	6	4	4500	178	1.2	511.25
E-n33-k4.evrp	32	1	6	4	8000	209	1.2	869.89
E-n51-k5.evrp	50	1	5	5	160	105	1.2	570.17
E-n76-k7.evrp	75	1	7	7	220	98	1.2	723.36
E-n101-k8.evrp	100	1	9	8	200	103	1.2	899.88
X-n143-k7.evrp	142	1	4	7	1190	2243	1.0	–
X-n214-k11.evrp	213	1	9	11	944	987	1.0	–
X-n352-k40.evrp	351	1	35	40	436	649	1.0	–
X-n459-k26.evrp	458	1	20	26	1106	929	1.0	–
X-n573-k30.evrp	572	1	6	30	210	1691	1.0	–
X-n685-k75.evrp	684	1	25	75	408	911	1.0	–
X-n749-k98.evrp	748	1	30	98	396	790	1.0	–
X-n819-k171.evrp	818	1	25	171	358	926	1.0	–
X-n916-k207.evrp	915	1	9	207	33	1591	1.0	–
X-n1001-k43.evrp	1000	1	9	43	131	1684	1.0	–

- `VEHICLES`: minimum number of EVs (or routes) a solution can have
- `DIMENSION`: the number of customers including the central depot
- `STATIONS`: the number of charging stations
- `CAPACITY`: the maximum cargo capacity of the EV (i.e., C)
- `ENERGY_CAPACITY`: the maximum battery charge of the EV (i.e., Q)
- `ENERGY_CONSUMPTION`: the constant charge consumption rate (i.e., h)
- `EDGE_WEIGHT_FORMAT`: euclidean distance
- `NODE_COORD_SECTION`: this section contains the information of the nodes, in the format of node id, x and y coordinates
- `DEMAND_SECTION`: this section contains the demands of each customer, in the format of node id and demand (i.e., q_i)
- `STATIONS_COORD_SECTION`: this section contains the node ids of the charging stations

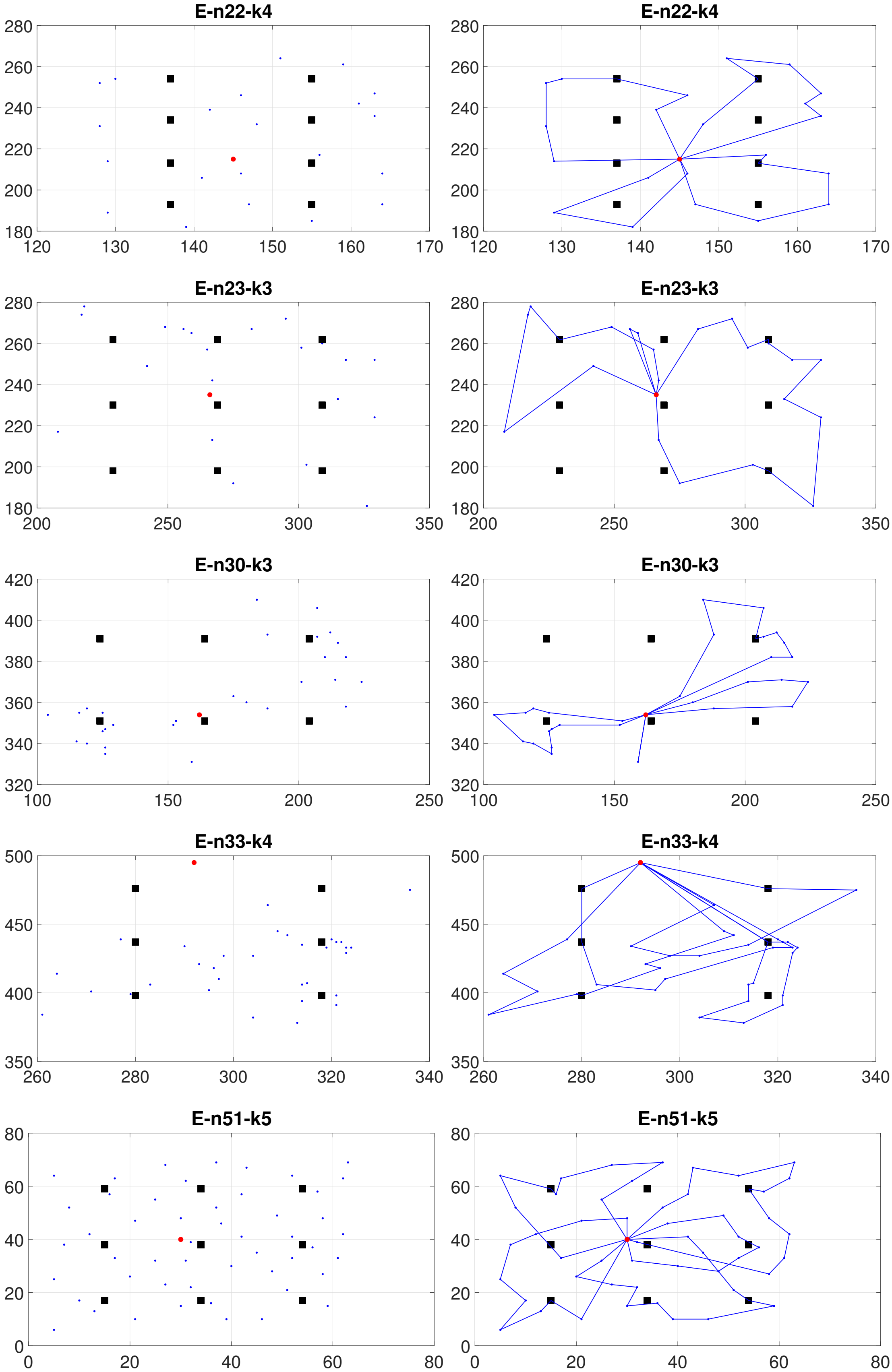

Figure 1: continued

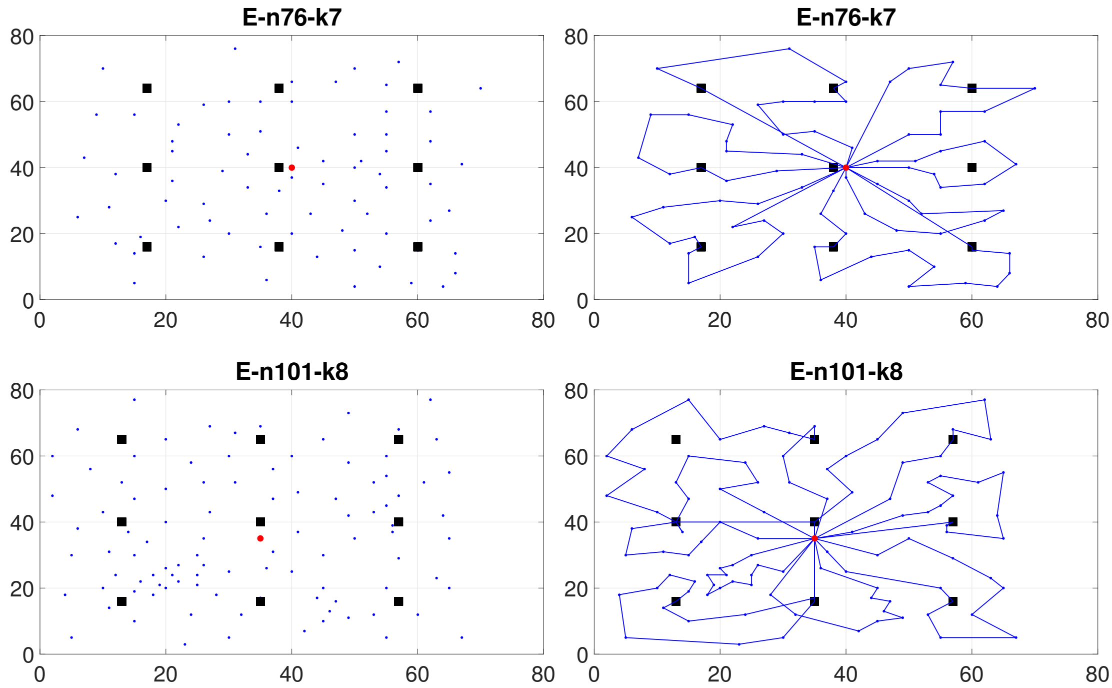

Figure 1: Illustration of problem instances (left) with the known upper bound solution (right). These problem instances are useful for testing purposes and parameter tuning. Note that the symbols: •, ·, and ■ represent the depot, customers and charging stations respectively.

In the competition website[2] a sample source code that is able to read all the aforementioned information (i.e., read the files with extension `.evrp`) is provided in the file (`EVRP.hpp`) and can be utilized through the corresponding functions. More specific, the functions implemented in `EVRP.hpp` can be used to generate the distance matrix of the EVRP instance, access all the aforementioned information, and evaluate the solution generated by a solver (note that the solution must be in a specific format described in the source code). Additionally, the implementation of file `stats.hpp` provides functions that can be used to save the results of the solver that can be submitted to the competition. It is strongly suggested to utilize the provided file `main.cpp` by simply replacing the `initialize_random_heuristic()` and `generate_random_solution()` with the implementation of another solver. Finally, the benchmark set described in Table 1 is also available at the completion website.

4 Evaluation Criteria

- **Problem Instances**: The 17 EVRP instances are summarized in Table 1

[2] `https://mavrovouniotis.github.io/EVRPcompetition2020/`

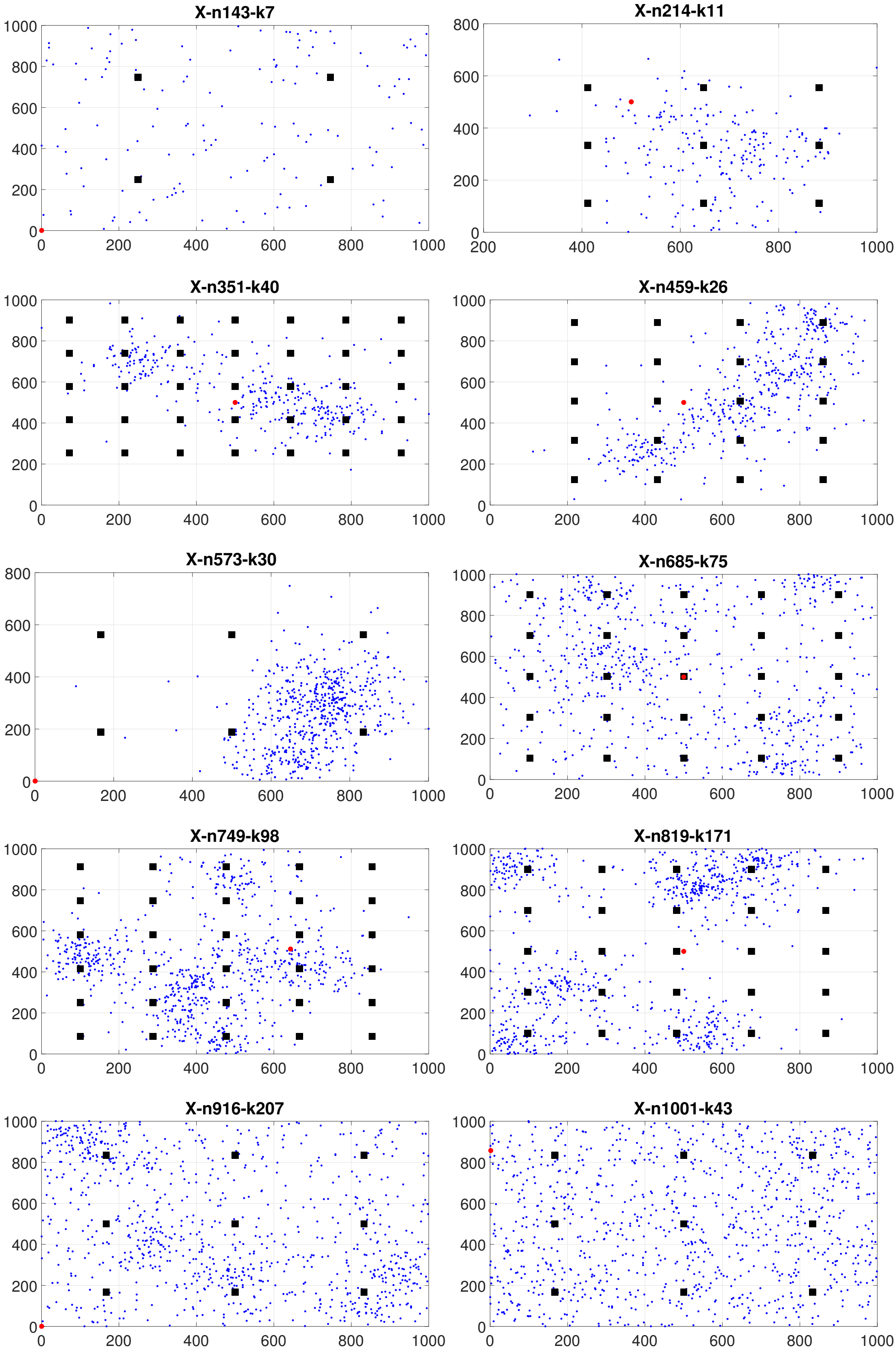

Figure 2: Illustration of problem instances with unknown upper bound. Note that the symbols: $\bullet$, $\cdot$, and $\blacksquare$ represent the depot, customers and charging stations respectively.

Table 2: Example – Random Heuristic results.

id	name	$\bar{P}$			
		mean	stdev	min	max
1	`E-n22-k4.evrp`	621.78	17.9	583.2	660.5
2	`E-n23-k3.evrp`	1037.14	35.1	961.4	1091.8
3	`E-n30-k3.evrp`	1129.5	36.6	1039.0	1196.3
4	`E-n33-k4.evrp`	1377.3	30.5	1303.4	1428.5
5	`E-n51-k5.evrp`	1550.6	23.9	1498.0	1592.6
6	`E-n76-k7.evrp`	2647.8	43.8	2531.3	2711.5
7	`E-n101-k8.evrp`	3707.1	40.8	3613.3	3808.2
8	`X-n143-k7.evrp`	78295.0	472.2	77983.2	79114.0
9	`X-n214-k11.evrp`	59075.0	601.1	57594.8	60019.4
10	`X-n352-k40.evrp`	164585.2	1117.9	161915.3	166531.5
11	`X-n459-k26.evrp`	215086.5	1522.0	212535.4	217665.8
12	`X-n573-k30.evrp`	180595.6	831.4	178858.2	182208.4
13	`X-n685-k75.evrp`	477112.4	1791.4	475149.2	479648.1
14	`X-n749-k98.evrp`	440276.3	3127.5	435556.8	443449.7
15	`X-n819-k171.evrp`	600816.5	4980.3	592333.4	605544.4
16	`X-n916-k207.evrp`	753955.5	1834.0	751370.8	756099.5
17	`X-n1001-k43.evrp`	637340.5	2361.7	634329.7	640461.2

- `DEPOT_SECTION`: this section contains the node id of the central depot
- **Independent Runs**: 20 (with seeds from $1-20$)
- **Evaluations**: The maximum number of evaluations is $25000n$ steps of $\mathcal{O}(n^2)$, where $n = |I| + 1 + |F'|$
- **Termination Condition**: When the algorithm reaches the maximum number of evaluations [in other words calling the objective function in Eq. (1)].
- **Measurement**: The best solution found from all evaluations averaged over multiple independent runs as follows:

$$\bar{P} = \frac{1}{R}\sum_{i=1}^{R} P_i^*, \qquad (10)$$

where R is the number of independent runs (i.e., $R = 20$), and P_i^* is the best solution found from all evaluations in run i.

NOTE: The $\bar{P}$ measurement is already implemented in the sample code and stored in output text files. Contestants can simply submit these output text files obtained for each instance together with the details and source code of their algorithm. Table 2 shows an example of the results obtained from the sample heuristic implemented in the source code (file `heuristic.hpp`), in which the "mean" is the average of the 20 runs, "stdev" is the standard deviation, "min" is the best result of the 20 runs, and "max" is the worst result of the 20 runs. All these values are calculated in the output text files generated by the provided source code.

5 Conclusion

In this report we have proposed a set of 17 EVRP benchmark instances to evaluate algorithms. The EVRP benchmark instances impose new challenges to the ordinary VRP problem since algorithms have to consider the possibility of de-routing to visiting a charging station for recharging while serving all the demands of the customers. The primary goal in generating this set of benchmark instances is to boost the research on the applications of the EVRP.

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