Solving electric vehicle-drone routing problem using memetic algorithm: supplementary material

1 Appendix: Decoding the solution scheme

Representing an EVDRP solution into a permutation-based scheme is one crucial part to tackle, which becomes another contribution of this research. Admittedly, the encoding and decoding process of EVDRP is more exhaustive than related problems, such as VRPD or EVRP. This is largely caused by the presence of recharging nodes, which could be used for multiple different purposes: recharging, launching and synchronizing. In addition, there are several problem-specific rules that need to be considered, such as that drones should not be able to visit a recharging node by themselves. Therefore, due to the complexity of the solution scheme, we present a dedicated part of this manuscript to provide a clear explanation of how to decode the solution scheme into a corresponding EVDRP solution.

As mentioned before, the proposed solution scheme is a permutation-based scheme that is widely used to represent routing problems (i.e. VRP). Such a scheme is generally decoded from left to right, where each step represents the movement of a vehicle from a node presented in i to the node presented in $i+1$. Regarding this, EVDRP involves two different transportation modes (EVs and drones), thus we need to record the positions of EV and drone in the current tour since not every step involves the movement of both modes (i.e. sortie). Therefore, we introduce two tuples to record the latest position of the current EV and the latest position of the current drone (i.e. LP_t and LP_d), in which their values are updated in each step. To illustrate, at the start of any tour, both LP_t and LP_d are set as '0'. Then, when the drone is launched from depot '0' to deliver a parcel for customer node '2', we record $LP_d = 2$ and $LP_t = 0$, since the current EV remains in depot '0'.

Overall, we derive 28 different possibilities that could occur from each decoding step. To ease the explanation, we divide them into four different classes: (i) start of a tour, (ii) end of a tour, (iii) entering a customer node during within a tour, and (iv) entering a recharging node during a tour.

The start of a tour occurs at the first step of the decoding process, or any steps which starts with '0' in U. In this part, we derive four different possible operations that might occur, as presented in Figure 1. It is worthwhile to see in Figure 1 that when the decoding step finds a customer node, there are two possible operations (both vehicles travel to the customer node together or sortie operation), meanwhile, at the case when the decoding step finds a recharging node, there is only one possible operation, since sorties should not visit a recharging station. In addition, we also present one important case where a tour consists of recharging node(s) without visiting any customer nodes (i.e. $U = [0, R, 0]$). In this regard, we set such a tour as an inactive tour and proceed to the next step.

On the other hand, a current tour is ended whenever the decoding step finds '0' in U. Figure 2 presents all possible operations that might incur at such event. From Figure 2, it is shown how tuples LP_t and LP_d could be used to differentiate multiple cases that might present from a single decoding step. Finally, the last two classes decode the movements executed within a tour. A tour is continued when the decoding step finds either a customer or recharging node in U. In this regard, we present all the possible operations respectively in Figures 3 and 4.

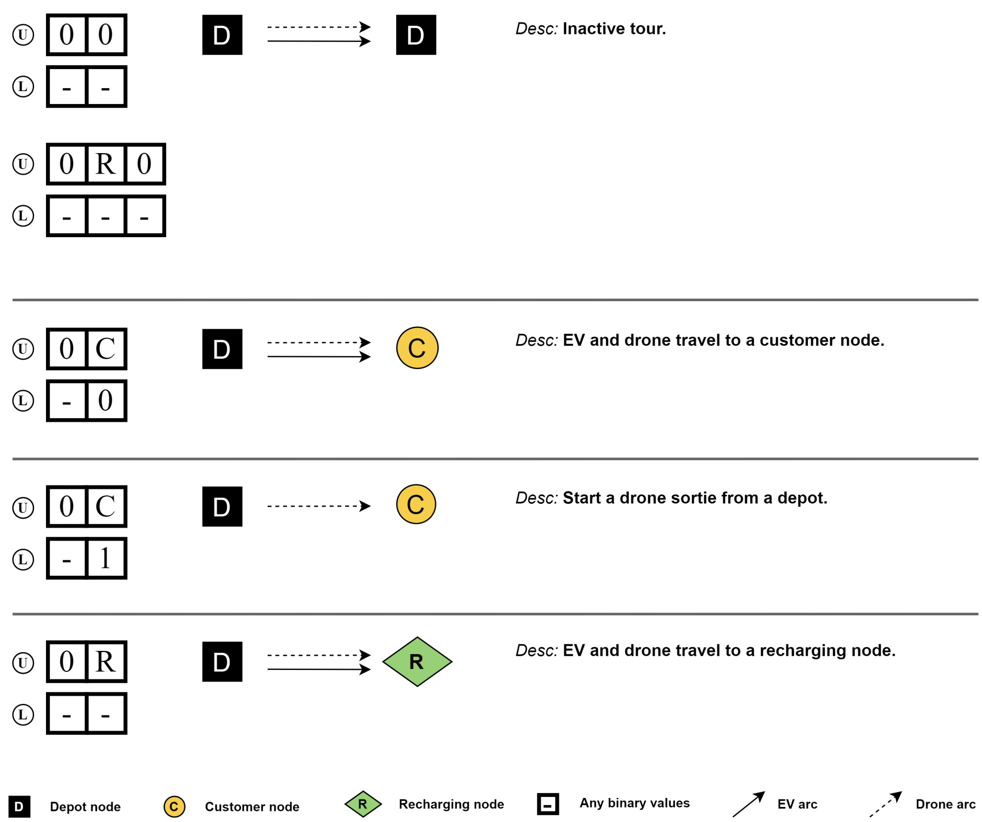

Figure 1: All possible operations at the start of a tour.

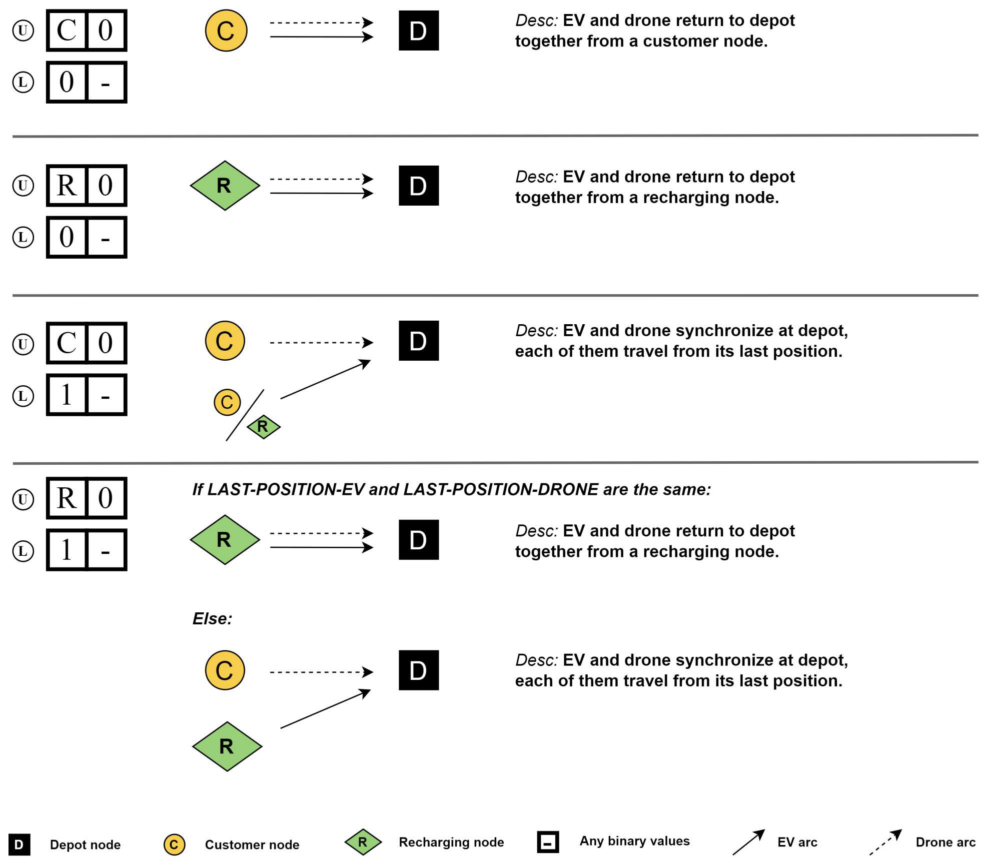

Figure 2: All possible operations at the end of a tour.

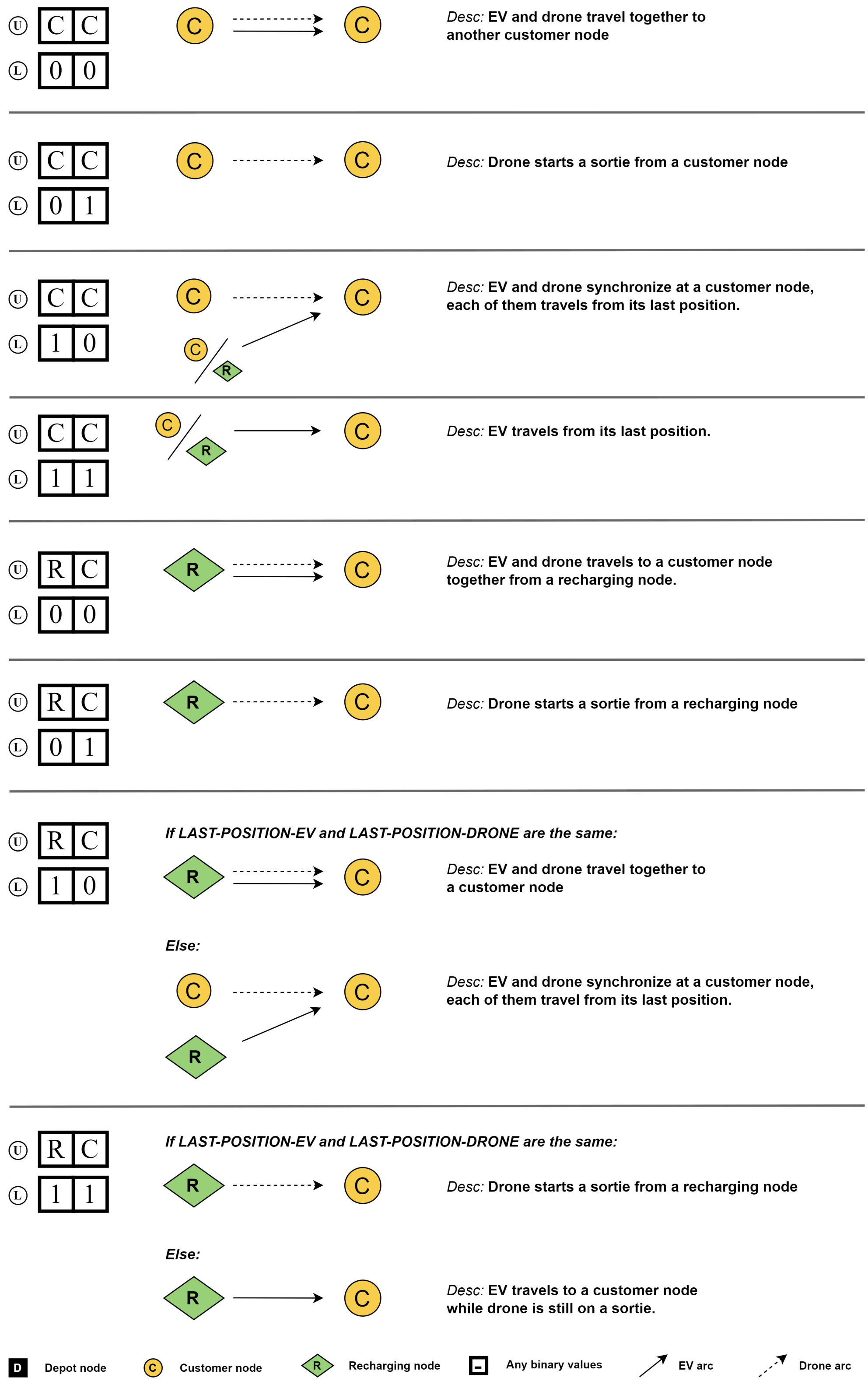

Figure 3: All possible operations rise from entering a customer node.

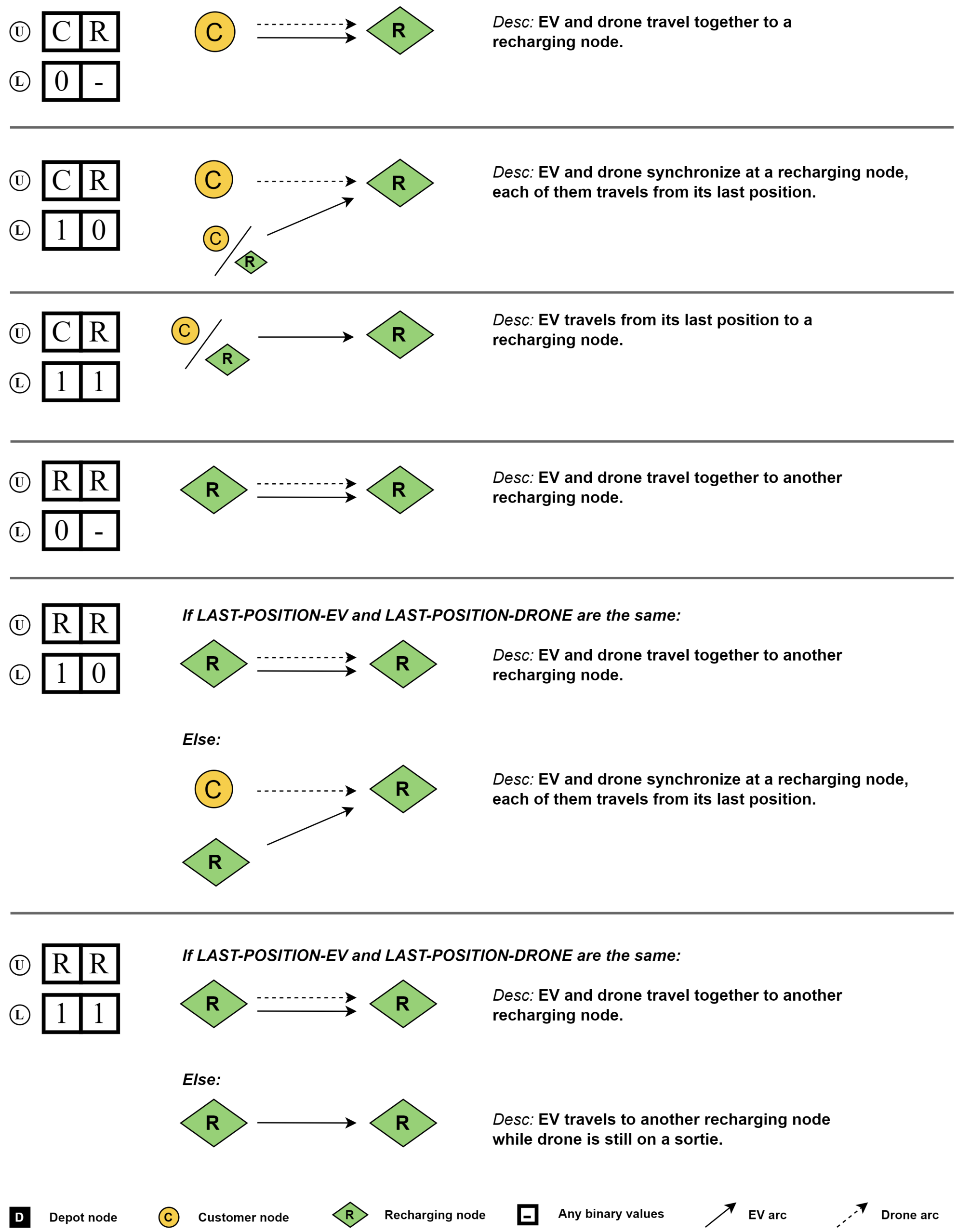

Figure 4: All possible operations rise from entering a recharging node.

2 Appendix: MILP formulation for TSP

The TSP sub-problem can be solved optimally as an integer programming formulation. Here, we present the classical formulation of TSP and modify the objective function into the minimization of total travel time.

First, for each generated cluster i, let us define:

- $T \subseteq V$ as a subset of all customer nodes included in cluster i and the depot node, $T = V_i^t \cup V_0$
- α as a set of (i, j) arcs in T, where $i \neq j$,
- $t_{i,j}$ as a time required (for EVs) to traverse through arc (i, j),
- s_j as a service time in node j,
- $\theta_{i,j}$ as a decision variable to decide if arc (i, j) is traversed or not,
- $\omega_{i,j}$ as an auxiliary variable to eliminate subtours.

Then, for each cluster i, the MILP for min-time TSP can be presented as follows.

$$Z_{TSP} = \sum_{i \in T \setminus \{j\}} \sum_{j \in \{T\} \setminus \{i\}} (t_{i,j} + s_j)\theta_{i,j} \tag{B.1}$$

subject to:

$$\sum_{i \in T \setminus \{j\}} \theta_{i,j} = 1 \qquad \forall\, j \in T \setminus \{i\} \tag{B.2}$$

$$\sum_{j \in T \setminus \{i\}} \theta_{i,j} = 1 \qquad \forall\, i \in T \setminus \{j\} \tag{B.3}$$

$$\omega_i - \omega_j + \theta_{i,j} \cdot |T| \leq |T| - 1 \qquad \forall\, 1 \leq i \neq j \leq |T| \tag{B.4}$$

$$1 \leq \omega_i \leq |T| \qquad \forall\, i \in T \setminus \{0\} \tag{B.5}$$

$$\theta_{i,j} \in \{0, 1\} \qquad \forall\, (i, j) \in \alpha \tag{B.6}$$

Objective function B.1 aims to minimize the total travel time of the tour. Equations B.2 and B.3 ensure that each customer node is visited only once and they also regulate the inbound and outbound arcs. Equation B.4 is used to eliminate subtours. Lastly, Equations B.5 and B.6 regulate the value of decision variables.

3 Appendix: Visualization of results

In order to demonstrate the applicability of our proposed MA for solving EVDRP, we visualize some solutions produced by MA here. For this purpose, we take one small-size instance (rc204C15_S7) and one large-size instance (c104_21) and present the tours created for these instances visually in Figures 5 and 6. Note that the black lines correspond to EV tours, while the red dotted lines correspond to drone sorties.

Figure 5 presents the visualization of a solution for rc204C15_S7. This instance comprises 15 customer nodes and 7 different recharging nodes that can be visited. The solution presented in Figure 5 has an objective value (total completion time) of $\sigma = 114.44$, and with the presented solution scheme, this solution can be represented as follows.

$U \longrightarrow$ [1, 19, 22, 13, 12, 14, 1, 8, 11, 1, 23, 10, 21, 9, 16, 1, 17, 15, 20, 18, 1, 8, 1]

$L \longrightarrow$ [0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0]

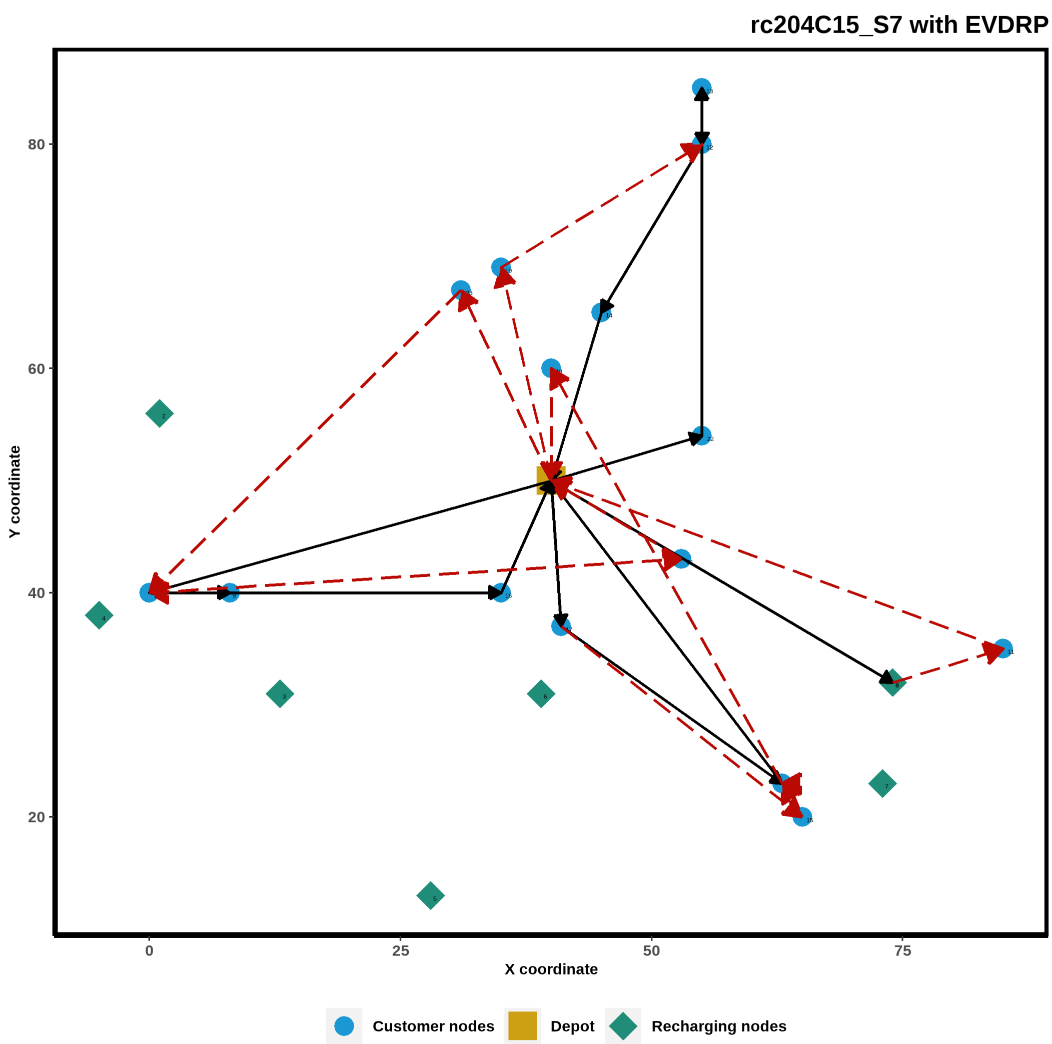

Figure 5: Solution visualization for rc204C15_S7.

On the other hand, Figure 6 visualizes the solution for a large-size instance rc204C15_S7, which comprises 100 customer nodes and 21 recharging nodes. The solution presented in Figure 6 has an objective value (total completion time) of $\sigma = 188.04$, and with the solution scheme presented in Appendix 1, this solution can be represented below.

$U \longrightarrow$ [1, 89, 65, 43, 44, 52, 45, 48, 50, 49, 47, 46, 51, 58, 57, 54, 60, 61, 59, 56, 1, 96, 87, 85, 84, 104, 103, 100, 93, 98, 92, 99, 95, 101, 102, 94, 83, 90, 86, 88, 91, 1, 3, 2, 3, 1, 55, 69, 71, 74, 68, 72, 70, 73, 67, 66, 62, 63, 64, 53, 79, 77, 76, 75, 78, 82, 80, 81, 1, 25, 27, 29, 30, 26, 23, 24, 28, 31, 32, 34, 33, 40, 37, 41, 38, 39, 36, 35, 121, 42, 1, 109, 112, 114, 105, 106, 115, 119, 116, 117, 122, 118, 120, 113, 111, 110, 107, 108, 97, 1]

$L \longrightarrow$ [0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0]

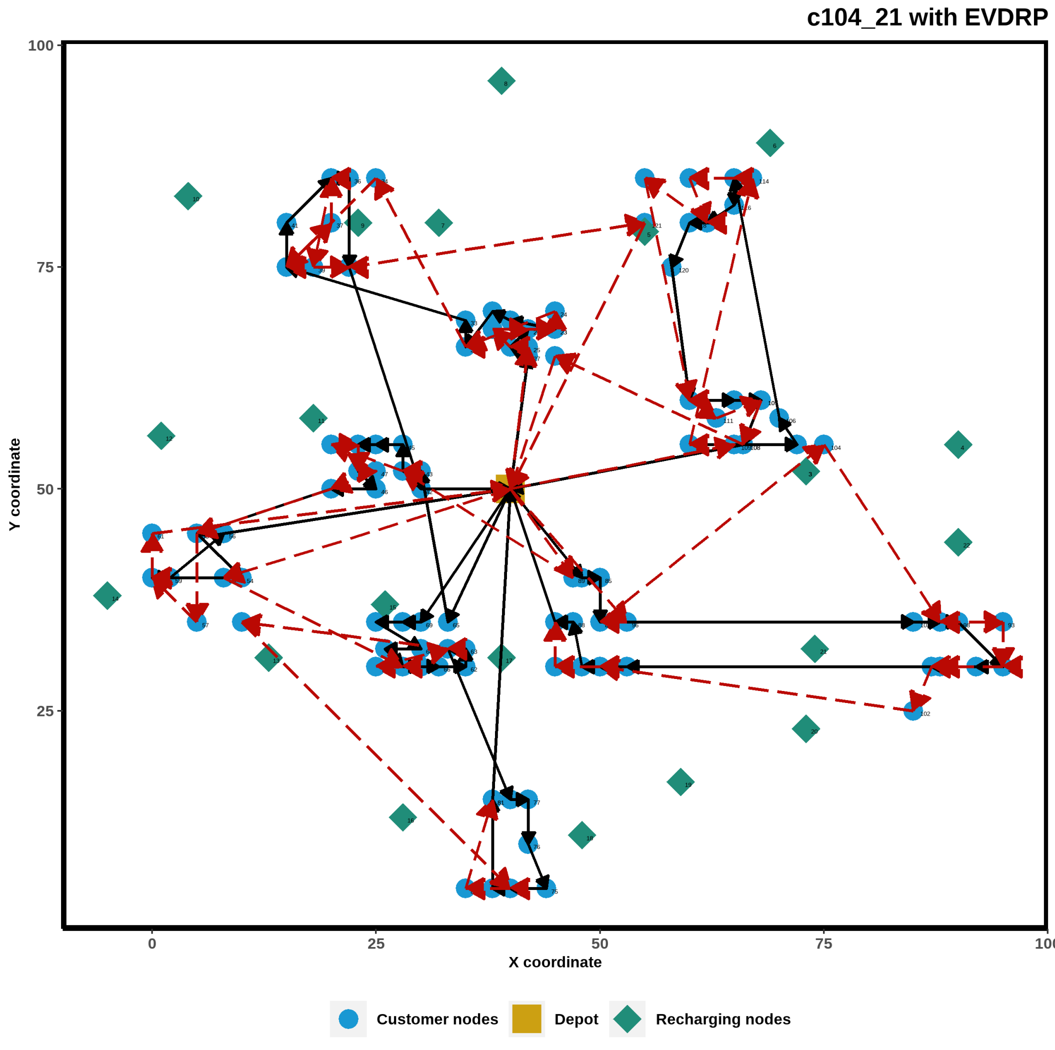

Figure 6: Solution visualization for c104_21.

4 Appendix: Experiment results for managerial discussions

Here, we present the experiment results related to managerial discussions. It is important to note that all the values presented in the following tables are based on the mean value of each variable. In accordance, we introduce the following notations:

- $\%VD$: Proportion of drone-eligible drones, in which 'Low' depicts instances with $\%VD \leq 50\%$ and 'High' depicts instances with $\%VD > 50\%$.
- D_t : Total distance traveled by GVs (either EVs or ICEVs) (km).
- D_d : Total distance traveled by drones (km).
- $\%D$: Proportion of customer nodes served by drones (%).
- RCT : Total recharging time of EVs (minutes).

Sensitivity analysis on drone parameters

Prob.	$\%VD$	v_d	v_t	E_d	E_t	R_t	Z	D_t	D_d	$\%D$	RCT
EVDRP	-	50	35	30	33	300	236.91	1390.17	433.95	20%	6.58
EVDRP	Low	50	35	30	33	300	244.71	1443.09	383.55	18%	7.22
EVDRP	High	50	35	30	33	300	228.53	1333.32	488.08	23%	5.90
EVDRP	-	50	35	55	33	300	233.93	1349.56	700.52	23%	6.06
EVDRP	Low	50	35	55	33	300	240.35	1400.57	590.34	20%	6.58
EVDRP	High	50	35	55	33	300	227.03	1294.77	818.87	27%	5.51
EVDRP	-	50	35	80	33	300	231.62	1321.53	838.52	25%	6.26
EVDRP	Low	50	35	80	33	300	237.71	1371.00	720.70	22%	7.14
EVDRP	High	50	35	80	33	300	225.08	1268.40	965.08	28%	5.32
EVDRP	-	30	35	55	33	300	247.89	1429.41	374.60	15%	6.77
EVDRP	Low	30	35	55	33	300	247.77	1452.08	309.91	13%	6.85
EVDRP	High	30	35	55	33	300	248.02	1405.06	444.08	18%	6.68
EVDRP	-	70	35	55	33	300	227.59	1312.87	891.89	26%	5.23
EVDRP	Low	70	35	55	33	300	236.11	1377.41	742.06	22%	5.51
EVDRP	High	70	35	55	33	300	218.43	1243.54	1052.81	29%	4.93

Sensitivity analysis on EV parameters

Prob.	$\%VD$	v_d	v_t	E_d	E_t	R_t	Z	D_t	D_d	$\%D$	RCT
EVDRP	-	50	35	55	18	300	241.14	1336.04	664.48	0.24	20.30
EVDRP	Low	50	35	55	18	300	242.80	1255.14	606.23	0.23	19.45
EVDRP	High	50	35	55	18	300	239.36	1422.93	727.04	0.25	21.21
EVDRP	-	50	35	55	33	300	233.93	1349.56	700.52	0.23	6.06
EVDRP	Low	50	35	55	33	300	240.35	1400.57	590.34	0.20	6.58
EVDRP	High	50	35	55	33	300	227.03	1294.77	818.87	0.27	5.51
EVDRP	-	50	35	55	48	300	231.96	1348.83	746.44	0.24	3.46
EVDRP	Low	50	35	55	48	300	234.58	1279.90	684.09	0.23	3.22
EVDRP	High	50	35	55	48	300	229.15	1422.86	813.41	0.25	3.72
EVDRP	-	50	35	55	33	50	239.38	1343.89	713.38	0.24	31.07
EVDRP	Low	50	35	55	33	50	240.85	1270.51	656.26	0.23	29.95
EVDRP	High	50	35	55	33	50	237.79	1422.70	774.72	0.25	32.27
EVDRP	-	50	35	55	33	150	233.75	1352.15	701.19	0.23	11.42
EVDRP	Low	50	35	55	33	150	234.61	1269.82	649.74	0.23	10.06
EVDRP	High	50	35	55	33	150	232.83	1440.59	756.45	0.24	12.88

Customer distribution

Prob.	**Dist.**	Z	D_t	D_d	$\%D$	RCT
EVDRP	Clustered	228.53	1288.18	577.70	0.21	4.68
EVDRP	Random	217.63	1324.58	793.57	0.26	5.52
EVDRP	Random-Clustered	263.09	1450.68	697.27	0.22	8.31

Comparison of EVDRP, EVRP, and VRPD

Prob.	$\%VD$	Z	D_t	D_d	$\%D$	RCT	$Z - RCT$
EVDRP	-	233.93	1349.56	700.52	0.23	6.06	227.86
EVDRP	Low	240.35	1400.57	590.34	0.20	6.58	233.77
EVDRP	High	227.03	1294.77	818.87	0.27	5.51	221.52
EVRP	-	242.47	1465.68	0.00	0.00	5.83	236.64
EVRP	Low	240.05	1464.11	0.00	0.00	5.57	234.48
EVRP	High	245.07	1467.36	0.00	0.00	6.10	238.97
VRPD	-	225.96	1234.59	727.72	0.23	0.00	225.96
VRPD	Low	231.96	1289.28	647.27	0.21	0.00	231.96
VRPD	High	219.51	1175.84	814.12	0.26	0.00	219.51