Greedy-Based Hybrid Metaheuristics for the Sustainable Electric Vehicle Routing Problem

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***Abstract*—The growing adoption of electric vehicles in urban logistics has increased the need for routing models that jointly address operational efficiency and environmental impact. This paper studies a Sustainable Electric Vehicle Routing Problem with Time Windows, which extends the classical EVRPTW by integrating mixed time windows with penalties and carbon-emission costs, while restricting each charging station to at most one visit per route and prohibiting depot-to-station and station-to-station movements. To solve this NP-hard problem, two greedy-based hybrid metaheuristics are proposed, Greedy Simulated Annealing (GSSA) and Greedy Variable Neighborhood Search (GSVNS). Computational experiments on 76 benchmark instances show that greedy-based hybridization significantly improves the baseline methods. GSSA achieves an average total-cost reduction of 49.48% over SA, while GSVNS improves VNS by 11.49% in total cost, 16.89% in distance, and 19.52% in fleet size. In addition, GSVNS attains the best total cost on 80.26% of the tested instances, confirming its effectiveness, particularly on large-scale instances.**

Keywords– Electric Vehicle Routing Problem, Sustainable Logistics, Carbon Emission Cost, Mixed Time Windows, Hybrid Metaheuristics, Simulated Annealing, Variable Neighborhood Search.

I. Introduction

The logistics and transportation sector is undergoing rapid changes. Increasing customer expectations and the demand for faster deliveries now add significant complexity to routing and scheduling. Among all logistics stages, last-mile delivery remains the most expensive and operationally constrained, as it concentrates challenges of performance, flexibility and sustainability [1]. At the same time, the decarbonization of transport has become a major policy and research priority. Road freight, still largely reliant on fossil fuels, is a major source of greenhouse gas emissions. To address this issue, public and industrial strategies increasingly promote the electrification of vehicle fleets. While electric vehicles (EVs) offer a promising alternative, they introduce new operational constraints such as limited driving range, charging requirements and highly variable energy consumption depending on real conditions (payload, elevation, temperature, traffic, etc.) [2]. Therefore, routing approaches must evolve from purely distance-based objectives toward energy and emission-aware decision-making.

Vehicle Routing Problems (VRPs) provide a framework to model these challenges [3]. However, most classical formulations still minimize traveled distance or fleet size, which poorly reflects real-world operational concerns [4]. Modern routing must incorporate operational constraints and environmental impact.

In this work, we propose a new variant of the EVRP, referred to as the Sustainable EVRP with Time Windows (SEVRPTW). Our model extends the EVRPTW of Schneider et al. [5] in two directions. First, it incorporates a carbon-emission cost into the objective function to account for the indirect CO_2 emissions associated with electric vehicle energy consumption. Second, it revises the routing assumptions by allowing mixed time windows with penalties, limiting each charging station to at most one visit per route, and prohibiting depot-to-station as well as station-to-station movements. To solve this NP-hard problem, we develop two greedy-based hybrid metaheuristics, GSSA and GSVNS. A constructive greedy phase first generates a feasible initial solution, which is then improved by Simulated Annealing (SA) and Variable Neighborhood Search (VNS), respectively.

The remainder of this paper is organized as follows. Section II reviews the literature on the EVRP and related solution approaches. Section III presents the proposed SEVRPTW formulation. Section IV describes the developed hybrid metaheuristics. Section V reports the experimental setup and computational results. Finally, Section VI concludes the paper and discusses future research directions.

II. Related Work

In this section, we review the existing literature on the EVRP, with a particular focus on the main solution approaches proposed to address it.

A. Environmentally Friendly Vehicle Routing Problem

The growing need to reduce the environmental impact of freight transportation has led to the emergence of Environmentally Friendly or Green Vehicle Routing Problems (EF-VRPs) [6]. Unlike classical routing models, EF-VRPs incorporate sustainability-related objectives such as reducing fuel consumption, energy use, or pollutant emissions, in addition to economic performance. A common strategy in this context is the use of alternative-fuel vehicles, including electric and hybrid vehicles [7]. These vehicles make it possible to reduce emissions in urban distribution, but they also introduce new operational constraints related to limited driving range, energy consumption, refueling or recharging operations and infrastructure availability. Among green routing problems, those involving EVs have received particular attention, especially in urban and last-mile logistics, because of their strong potential for improving energy efficiency and reducing emissions. This has led to the development of the EVRP as a major research direction [8].

B. Electric Vehicle Routing Problem

The EVRP is a specific subclass of the EF-VRP in which the fleet consists exclusively of EVs. In addition to the classical constraints of the VRP, the EVRP integrates battery-related limitations such as restricted driving range, state-of-charge management, charging station locations and charging durations [9]. EVRP does not focus solely on minimizing travel distance or operational cost, but instead seeks a balance between operational efficiency and environmental sustainability [10]. Figure 1 shows an illustrative example of an EVRP instance.

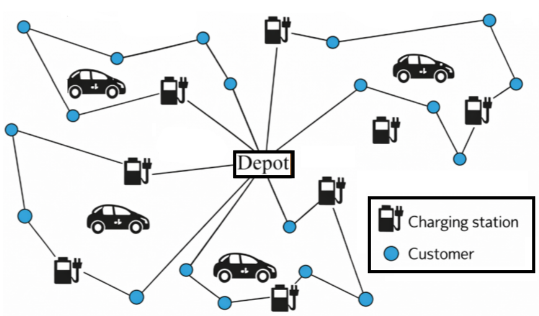

Figure 1. Illustrative example of an EVRP instance showing the depot, customer locations, charging stations, and vehicle routes.

Several EVRP variants have been proposed to better capture real-world logistics operations. Among the most extensively studied variants is EVRP with Time Windows (EVRPTW), where customer services must be performed within predefined temporal intervals [5]. Energy-related assumptions have been also refined by integrating different charging strategies such as partial charging [11] or battery swapping [12]. Although EVRP variants differ in their assumptions and constraints, many of them mainly address operational and energy-related issues, while environmental aspects are not explicitly taken into account. This highlights the need for routing models that directly integrate carbon footprint and CO_2 emission considerations.

C. Existing EVRP Solution Methods

The EVRP and its variants have attracted growing research interest, leading to many mathematical models and solution methods. Exact approaches, such as those proposed in [13, 14], are still useful for small and medium size instances and often serve as benchmarks. However, because the EVRP is NP-hard, these methods face major scalability issues and become impractical for large instances. For this reason, recent studies have mainly focused on heuristic and metaheuristic methods, including Variable Neighborhood Search [15], Genetic Algorithms [16] and Adaptive Large Neighborhood Search [17]. These approaches generally provide good-quality solutions within reasonable computation times. More recently, hybrid methods have received increasing attention. Since metaheuristics are stochastic and do not guarantee optimality, they are often combined with other heuristic, metaheuristic, or AI-based components to improve the initial solution, guide the search more effectively, and accelerate convergence [18, 19, 20, 21]. Despite these advances, many EVRP studies still rely on simplified assumptions, especially regarding energy use and environmental impact. This highlights the need for more realistic EVRP models that jointly consider operational constraints and carbon-emission issues while remaining solvable for large-scale applications.

III. Sustainable Electric Vehicle Routing Problem

We introduce the SEVRPTW, an extension of the classical EVRP that integrates two key features often neglected in traditional formulations. First, the model allows mixed time windows, where early and late arrivals are tolerated within prescribed bounds and penalized in the objective function. Second, it explicitly accounts for environmental impact by incorporating a carbon-emission cost. In this way, the SEVRPTW seeks to balance operational efficiency, service quality and environmental sustainability. Our formulation builds upon the EVRPTW model of Schneider et al. [5], whose objective is to minimize the total traveled distance:

$$\min \sum_{i \in V_0} \sum_{j \in V_{n+1}, i \neq j} d_{ij}\, x_{ij} \tag{1}$$

While this formulation provides a relevant basis for EVRPTW, a distance-minimization objective alone does not adequately capture the indirect carbon impact associated with vehicle energy consumption, nor does it reflect the operational flexibility induced by penalized time-window violations. For this reason, we extend the EVRPTW model of Schneider et al. [5] to define the proposed SEVRPTW. Our model also differs from [5] in the treatment of charging station visits. Unlike Schneider et al. [5], who allow multiple visits to the same physical station through duplicated nodes, we restrict each charging station to at most one visit per route. This assumption better reflects real delivery operations, where repeated visits to the same station are unlikely and inefficient. In addition, depot-to-station and station-to-station movements are not allowed. Since vehicles leave the depot with a fully charged battery, charging is only performed when necessary during the route.

A. Sets

$D = \{0\}$	Depot
$S = \{1, \ldots, n_s\}$	Charging stations
$C = \{n_s + 1, \ldots, n_s + n_c\}$	Customers
$N = D \cup S \cup C$	All nodes
$A = \{(i, j) : i, j \in N, i \neq j\}$	Arcs

B. Parameters

d_{ij}	Distance between nodes i, j
h	Energy consumption rate (kWh/km)
v	Vehicle speed
p_c	Carbon price (/kgCO_2)
γ_e	Emission factor (kgCO_2/kWh)
$[e_j, l_j]$	Time window at customer j
β_a, β_r	Early/late penalty costs

C. Decision Variables

$x_{ij} \in \{0,1\}$	1 if arc (i,j) is used
$t_j \geq 0$	Arrival time at node j
$\varepsilon_j \geq 0$	Remaining energy at j
$a_j, r_j \geq 0$	Early/late deviations

D. Mathematical formulation

The objective function minimizes the total delivery cost composed of fixed vehicle usage, energy expenditure, time-window penalties and carbon impact:

$$\begin{aligned} \min Z = c_f & \sum_{j \in N \setminus \{0\}} x_{0j} && \text{(dispatching cost)} \\ & + \sum_{j \in C} (\beta_a \, a_j + \beta_r \, r_j) && \text{(time penalties)} \\ & + p_c \, \gamma_e \sum_{(i,j) \in A} h \, d_{ij} \, x_{ij} && \text{(carbon cost)} \end{aligned} \tag{2}$$

The SEVRPTW is subject to the following constraints:

$$\sum_{j \in N \setminus \{i\}} x_{ij} = 1 \quad \forall i \in C \tag{3}$$

$$\sum_{i \in N \setminus \{j\}} x_{ij} = \sum_{k \in N \setminus \{j\}} x_{jk} \quad \forall j \in N \setminus \{0\} \tag{4}$$

$$\sum_{j \in N \setminus \{i\}} x_{ij} \leq 1 \quad \forall i \in S \tag{5}$$

$$x_{0j} = 0 \quad \forall j \in S \tag{6}$$

$$x_{ij} = 0 \quad \forall (i,j) \in S \times S \tag{7}$$

$$t_i + (\tau_{ij} + \sigma_i) x_{ij} - M(1 - x_{ij}) \leq t_j \quad \forall (i,j) \in A, \; i \in C \cup \{0\} \tag{8}$$

$$t_i + \tau_{ij} x_{ij} + g\,(B - \varepsilon_i) - M(1 - x_{ij}) \leq t_j \quad \forall (i,j) \in A, \; i \in S \tag{9}$$

$$t_j + a_j \geq e_j \quad \forall j \in C \tag{10}$$

$$t_j - r_j \leq l_j \quad \forall j \in C \tag{11}$$

$$0 \leq a_j \leq A^{\max}, \qquad 0 \leq r_j \leq R^{\max} \quad \forall j \in C \tag{12}$$

$$y_j \leq y_i - q_i x_{ij} + Q_c(1 - x_{ij}) \quad \forall (i,j) \in A \tag{13}$$

$$\varepsilon_j \leq \varepsilon_i - h \, d_{ij} \, x_{ij} + B(1 - x_{ij}) \quad \forall (i,j) \in A \tag{14}$$

$$\varepsilon_j \leq B - h \, d_{ij} \, x_{ij} \quad \forall (i,j) \in A, \; j \in S \tag{15}$$

$$y_0 \leq Q_c \tag{16}$$

$$\varepsilon_0 = B \tag{17}$$

The constraints defined above enforce the feasibility of any SEVRPTW solution. Constraint (3) guarantees that each customer is visited exactly once, while constraint (4) ensures flow conservation by forcing every arrival at a node to be followed by a departure. Constraint (5) limits the number of visits to each charging station to at most one per route. Constraints (6) and (7) prohibit direct depot-to-station and station-to-station moves, respectively, which eliminates non-productive battery use. Constraints (8) and (9) propagate arrival times after service or charging operations using a big-M formulation, where M = max(l_j) + max(e_{ij} + t_j) provides a tight upper bound on arrival times and ensures that inactive arcs do not restrict feasible solutions. Constraints (10) to (12) implement mixed time windows by allowing bounded earliness and tardiness under penalty. Constraint (13) updates the remaining payload after each delivery, while constraint (14) accounts for the energy consumed along each traveled arc. Constraint (15) enforces battery capacity consistency at charging stations. Finally, constraints (16) and (17) establish initial load and energy conditions at the depot.

IV. Greedy-Based Hybrid Solution Framework

The SEVRPTW extends the EVRPTW, which is an NP-hard problem [5]. For such problems, metaheuristics are widely used because they can provide high-quality solutions within reasonable computation times, although they do not guarantee optimality. However, their performance depends strongly on how the search is guided and diversified. In the EVRPTW literature, Schneider et al. [5] showed the effectiveness of a hybrid neighborhood-based search, while SA is well known for its ability to escape local optima through the probabilistic acceptance of non-improving moves [22]. VNS in turn, relies on systematic changes of neighborhood structures to intensify and diversify the search [23]. Motivated by these advantages, we investigate both SA and VNS as solution methods and then combine them with a greedy construction phase. In this work, the greedy constructive phase generates a feasible initial solution by building a giant customer sequence based on spatial proximity and temporal priority, and then splitting it into feasible routes under capacity, battery and time-window constraints, as described in Algorithm 1. This provides a starting point for the search and reduces the risk of exploring poor-quality regions of the solution space. The initial solution is then improved using either SA or VNS. SA is adopted for its ability to accept non-improving moves and escape local optima, while VNS is used for its exploration of multiple neighborhoods and its strong intensification capability.
The computational performance of the proposed methods is evaluated in the next section.

V. Experiments & Results

A. Experiments

The algorithms were implemented in Python 3.11.9 and tested on a 12th Gen Intel i5-12450H processor with 16 GB of RAM under Windows 11. Computational tests were performed on the

EVRPTW benchmark of Schneider et al. [5], which includes clustered (C), random (R), and mixed (RC) instances with 5 to 100 customers and 2 to 21 charging stations. Table I summarizes the parameter values used in the SEVRPTW model.

Table I
SEVRPTW MODEL PARAMETERS

Parameter & Description	Value
c_f : Fixed vehicle operating cost	250
C_p : Unit cost of CO_2 emissions	0.1
β_a : Early arrival penalty coefficient per minute	0.3
β_r : Late arrival penalty coefficient per minute	0.8
γ_e : CO_2 emission factor	0.7
$A_{\max}$: Maximum allowable early arrival time in minutes	10
$R_{\max}$: Maximum allowable delay in minutes	15

Algorithm 1: Greedy Constructive Heuristic

Input : Depot d, customer set C, parameter k, and cost parameters
Output: Initial solution S

$GR \leftarrow \emptyset$
$S \leftarrow \emptyset$
while $|GR| < |C|$ **do**
  $U \leftarrow \{n \in C \mid n \notin GR\}$
  if $GR = \emptyset$ **then**
    Sort U by increasing distance from the depot d
  else
    Sort U by increasing distance from the last customer in GR
  Keep only the first k=5 customers of U
  Select $s \in U$ with the smallest due date (or ready time)
  Append s to GR
$i \leftarrow 1$
while $i \leq |GR|$ **do**
  $bestCost \leftarrow +\infty$
  $bestRoute \leftarrow \emptyset$
  $bestIndex \leftarrow i$
  for $j \leftarrow i$ **to** $|GR|$ **do**
    Construct route r from the subsequence $GR[i:j]$
    if r *is infeasible* **then**
      break
    Compute the cost $C(r)$
    if $C(r) < bestCost$ **then**
      $bestCost \leftarrow C(r)$
      $bestRoute \leftarrow r$
      $bestIndex \leftarrow j$
  Add $bestRoute$ to S
  $i \leftarrow bestIndex + 1$
return S

B. Results & Discussion

The detailed computational results for SA, GSSA, VNS, and GSVNS are reported in Tables II-V corresponding respectively to small instances and large instances of types C, R and RC. For each instance, the tables report the traveled distance, the number of vehicles, the carbon cost, the tardiness cost, the total cost and the CPU time. The total cost is computed as follows:

$$\mathit{TotalCost} = c_f \times \mathit{Veh.} + \mathit{CostCarbon} + \mathit{CostTardiness} \quad (18)$$

Table VI summarizes the pairwise comparisons between GSSA and SA, and between GSVNS and VNS, over the 76 benchmark instances. Since all reported metrics are minimized, a negative gap indicates that the hybrid method outperforms its corresponding baseline.

The results show that the greedy-based hybridization significantly improves both baseline metaheuristics. In particular, GSSA improves SA in 75 out of 76 instances in terms of total cost, with an average gap of -49.479%. Similarly, GSVNS outperforms VNS with negative mean gaps for distance (-16.889%), carbon cost (-16.894%), fleet size (-19.518%), and total cost (-11.485%). For fleet size, GSVNS improves VNS in 49 instances, with 21 ties and only 6 worse cases.

At the instance level, the benefit of hybridization is already visible on small instances, although some medium-size cases remain favorable to VNS. On large instances, GSVNS emerges as the most competitive method and achieves the lowest total cost in most cases across the C, R, and RC type. This confirms that combining greedy initialization with neighborhood exploration becomes increasingly effective as problem size grows. Overall, GSVNS attains the best total cost in 61 instances (80.263%), followed by GSSA in 22 instances, VNS in 13 instances and SA in 1 instance. These results show that greedy initialization significantly strengthens both SA and VNS, while GSVNS delivers the best overall performance.

VI. CONCLUSION

This paper addressed a new variant of EVRPTW, which incorporates carbon-emission cost, mixed time windows with penalties and revised charging assumptions. To solve this NP-hard problem, we proposed two greedy-based hybrid metaheuristics, GSSA and GSVNS. Both methods combine a greedy constructive phase, used to generate a feasible initial solution, with a metaheuristic improvement phase based on SA or VNS. The greedy initialization provides a starting point for the search, while the metaheuristic phase improves solution quality through diversification and intensification mechanisms. Computational experiments on the benchmark instances of Schneider et al. [5] showed that greedy-based hybridization significantly improves the performance of the baseline metaheuristics. In particular, GSSA clearly improves SA, while GSVNS emerges as the most effective method overall, especially on large instances. Overall, the proposed approach provides an effective solution framework for the SEVRPTW.

Future work may extend this study by considering heterogeneous fleets, stochastic energy consumption and nonlinear charging behavior.

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Table II
DETAILED COMPUTATIONAL RESULTS OF SA, GSSA, VNS, AND GSVNS FOR SMALL INSTANCES.

Instance	SA						GSSA						VNS						GSVNS					
	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU
c101C5	292.44	3	5.12	0.00	755.12	0.08	296.09	2	5.18	0.00	**505.18**	0.93	292.44	3	5.12	0.00	755.12	0.05	296.09	2	5.18	0.00	505.18	0.64
c103C5	176.05	2	3.08	0.00	503.08	0.19	167.11	2	2.92	0.00	**502.92**	1.38	176.05	2	3.08	0.00	503.08	0.05	167.11	2	2.92	0.00	502.92	0.60
c206C5	265.97	2	4.65	0.00	504.65	0.24	293.73	1	5.14	50.77	**305.91**	2.22	265.97	2	4.65	0.00	504.65	0.17	293.73	1	5.14	50.77	**305.91**	0.99
r105C5	197.77	4	3.46	0.00	1003.46	0.08	175.88	2	3.08	97.20	600.28	2.73	168.47	3	2.95	0.00	752.95	0.15	175.88	2	3.08	97.20	**600.28**	0.54
r202C5	204.04	5	3.57	292.82	1546.39	0.08	191.56	2	3.35	0.00	**503.35**	3.47	207.89	2	3.64	0.00	503.64	0.13	191.56	2	3.35	0.00	503.35	0.50
r203C5	210.76	2	3.69	43.80	547.49	0.07	251.16	2	4.40	0.00	504.40	3.51	259.93	2	4.55	0.00	504.55	0.15	251.16	2	4.39	0.00	**504.39**	0.53
rc105C5	239.80	1	4.20	645.12	899.31	0.11	253.03	2	4.43	71.09	575.52	4.34	253.60	4	4.44	0.00	1004.44	0.18	253.03	2	4.43	71.09	**575.52**	1.06
rc108C5	250.60	1	4.39	368.64	623.02	0.07	276.93	2	4.85	16.82	521.67	3.56	351.21	3	6.15	0.00	756.15	0.16	276.93	2	4.85	16.82	**521.67**	0.55
rc204C5	198.12	1	3.47	0.00	253.47	0.08	185.44	1	3.25	0.00	253.25	1.48	198.12	1	3.47	0.00	253.47	0.19	185.44	1	3.24	0.00	**253.24**	0.55
rc208C5	194.55	1	3.41	53.19	306.59	0.06	197.50	1	3.46	0.00	253.46	2.00	223.85	2	3.92	0.00	503.92	0.11	197.50	1	3.45	0.00	**253.45**	0.75
c103C15	569.70	6	9.97	0.00	1509.97	1.95	466.74	6	8.17	0.00	1508.17	5.42	519.10	5	9.08	99.44	**1358.52**	0.41	466.74	6	8.16	0.00	1508.16	4.57
c106C15	481.72	5	8.43	0.00	1258.43	0.56	359.55	5	6.29	0.00	1256.29	5.13	438.51	5	7.67	0.00	1257.67	1.31	353.27	5	6.18	0.00	**1256.18**	4.70
c208C15	521.02	4	9.12	0.00	1009.12	0.50	488.91	5	8.56	0.00	1258.56	19.91	520.36	4	9.11	0.00	**1009.11**	1.10	473.36	5	8.28	0.00	1258.28	5.66
r102C15	647.09	10	11.32	0.00	2511.32	0.54	473.07	4	8.28	492.82	1501.10	33.30	620.75	9	10.86	0.00	2260.86	1.06	473.07	4	8.27	492.82	**1501.09**	3.45
r105C15	498.02	8	8.72	0.00	2008.72	0.74	448.82	5	7.85	343.04	1600.89	8.43	481.81	7	8.43	0.00	1758.43	1.61	454.29	5	7.95	88.50	**1346.45**	5.38
r202C15	491.63	2	8.60	3015.58	3524.18	1.03	479.67	4	8.39	0.00	1008.39	9.38	588.11	3	10.29	0.00	**760.29**	1.36	479.67	4	8.39	0.00	1008.39	4.87
r209C15	599.06	3	10.48	997.43	1757.92	0.60	563.52	4	9.86	0.00	1009.86	11.12	549.70	3	9.62	0.00	**759.62**	1.46	563.52	4	9.86	0.00	1009.86	3.00
rc103C15	501.91	2	8.78	4164.53	4673.31	0.79	474.21	4	8.30	392.04	1400.34	6.80	570.77	7	9.99	0.00	1759.99	1.06	474.21	4	8.29	392.04	**1400.33**	4.05
rc202C15	488.09	2	8.54	3446.31	3954.85	0.71	507.20	3	8.88	207.44	966.32	9.44	684.29	5	11.98	0.00	1261.98	1.08	507.20	3	8.87	207.44	**966.31**	2.24
rc204C15	459.41	2	8.04	718.59	1226.63	1.02	418.54	2	7.32	49.82	**557.14**	9.03	552.92	3	9.68	0.00	759.68	1.91	418.54	2	7.32	49.82	557.14	3.02

Table III
DETAILED COMPUTATIONAL RESULTS OF SA, GSSA, VNS, AND GSVNS FOR LARGE C-TYPE INSTANCES

Instance	SA						GSSA						VNS						GSVNS					
	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU
c101_21	2832.03	35	49.56	0.00	8799.56	36.07	1713.75	21	29.99	614.11	5894.10	238.90	2402.74	26	42.05	0.00	6542.05	31.09	1548.34	18	27.09	572.83	**5099.92**	110.65
c102_21	2771.48	34	48.50	0.00	8548.50	55.31	1721.27	21	30.12	392.05	5672.17	225.71	2427.29	25	42.48	56.90	6349.38	27.24	1513.78	17	26.49	291.99	**4568.48**	55.80
c103_21	2606.18	29	45.61	0.00	7295.61	52.05	1472.94	16	25.78	1082.42	5108.20	243.37	2310.27	23	40.43	0.00	5790.43	69.15	1380.21	14	24.15	833.56	**4357.71**	45.72
c104_21	2098.29	21	36.72	44.26	5330.98	50.23	1454.91	16	25.46	572.38	4597.84	267.13	2057.33	20	36.00	44.26	5080.26	92.83	1379.47	14	24.14	572.38	**4096.52**	40.83
c105_21	2593.85	30	45.39	0.00	7545.39	15.42	1584.59	18	27.73	622.43	5150.16	228.60	2264.15	24	39.62	50.40	6090.02	91.70	1482.58	16	25.94	622.43	**4648.37**	55.17
c106_21	2529.30	28	44.26	0.00	7044.26	15.40	1532.19	18	26.81	572.93	5099.74	229.41	2140.46	22	37.46	0.00	5537.46	79.03	1443.25	16	25.25	573.34	**4598.59**	32.20
c107_21	2535.92	27	44.38	0.00	6794.38	15.30	1562.39	18	27.34	242.73	4770.07	228.64	2306.09	23	40.36	2.40	5792.76	70.86	1440.33	16	25.20	240.95	**4266.15**	31.53
c108_21	2132.51	23	37.32	0.00	5787.32	15.42	1312.97	14	22.98	645.09	4168.07	226.90	2002.25	20	35.04	0.00	5035.04	72.11	1256.03	14	21.98	544.67	**4066.65**	50.27
c109_21	2091.96	20	36.61	0.00	5036.61	15.42	1249.83	13	21.87	116.63	**3388.50**	249.97	2075.43	19	36.32	77.39	4863.71	87.59	1247.62	13	21.83	191.91	3463.74	133.07
c201_21	2353.19	19	41.18	0.00	4791.18	30.60	853.31	7	14.93	349.54	**2114.47**	465.52	1537.43	12	26.91	0.00	3026.91	109.27	836.31	7	14.63	350.54	2115.17	158.77
c202_21	2454.79	16	42.96	0.00	4042.96	61.22	1192.79	10	20.87	538.25	3059.12	840.87	1866.36	12	32.66	24.31	3056.97	92.55	1108.51	9	19.39	291.55	**2560.94**	155.67
c203_21	2184.01	15	38.22	0.00	3788.22	109.07	1202.16	9	21.04	465.27	2736.31	927.40	1767.38	11	30.93	0.00	2780.93	85.00	1115.91	9	19.52	291.17	**2560.69**	168.93
c204_21	1589.52	10	27.82	0.00	2527.82	102.50	1064.54	9	18.63	0.00	2268.63	721.18	1291.81	8	22.61	0.00	2022.61	98.59	942.43	8	16.49	0.00	**2016.49**	234.25
c205_21	1688.95	12	29.56	0.00	3029.56	108.04	809.40	7	14.17	96.13	1860.30	358.27	1392.48	10	24.37	0.00	2524.37	123.32	788.57	6	13.80	96.13	**1609.93**	191.92
c206_21	1446.42	10	25.31	0.00	2525.31	109.39	858.86	7	15.03	0.00	1765.03	349.20	1407.10	9	24.62	0.00	2274.62	92.12	819.05	6	14.33	0.00	**1514.33**	165.95
c207_21	1548.51	10	27.10	0.00	2527.10	78.49	1041.18	8	18.22	194.95	2213.17	339.64	1381.29	9	24.17	0.00	2274.17	95.14	897.64	7	15.70	194.95	**1960.65**	154.75
c208_21	1416.30	9	24.79	0.00	2274.79	30.59	844.92	7	14.79	0.00	1764.79	357.69	1305.45	8	22.85	0.00	2022.85	88.44	760.55	6	13.31	0.00	**1513.31**	198.04

Table IV
DETAILED COMPUTATIONAL RESULTS OF SA, GSSA, VNS, AND GSVNS FOR LARGE R-TYPE INSTANCES

Instance	SA						GSSA						VNS						GSVNS					
	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU
r101_21	3332.98	50	58.33	7.74	12566.07	17.67	2103.09	23	36.80	2057.14	7843.94	266.92	2963.62	40	51.86	14.46	10066.32	65.90	1990.67	21	34.83	2214.68	**7499.51**	91.57
r102_21	2845.74	41	49.80	6.93	10306.73	18.12	1815.43	19	31.77	1775.33	6557.10	281.12	2550.29	33	44.63	26.31	8320.94	74.10	1817.44	19	31.80	1728.72	**6510.52**	64.60
r103_21	2675.24	36	46.82	76.36	9123.18	17.93	1718.37	16	30.07	1583.23	5613.30	318.94	2452.79	31	42.92	76.36	7869.28	78.12	1707.28	16	29.87	1464.77	**5494.64**	92.62
r104_21	2077.60	25	36.36	10.19	6296.55	17.30	1641.58	14	28.73	922.10	4450.83	312.37	1913.84	22	33.49	10.19	5543.68	67.07	1641.58	14	28.72	922.10	**4450.82**	51.69
r105_21	2431.90	33	42.56	0.00	8292.56	17.53	1990.85	22	34.84	1497.02	7031.86	270.06	2321.75	29	40.63	0.20	7290.83	64.57	1902.11	20	33.28	1577.01	**6610.29**	94.56
r106_21	2269.65	29	39.72	33.61	7323.33	17.74	1900.58	19	33.26	1296.24	6079.50	289.35	2175.51	27	38.07	33.61	6821.68	68.79	1906.44	19	33.36	1235.85	**6019.21**	66.31
r107_21	2189.54	28	38.32	0.00	7038.32	17.05	1708.79	17	29.90	1020.18	5300.08	263.33	2057.25	25	36.00	0.00	6286.00	80.63	1656.00	16	28.98	1070.48	**5099.46**	62.78
r108_21	1868.62	22	32.70	21.32	5554.02	17.27	1642.34	14	28.74	632.71	**4161.45**	308.11	1835.63	22	32.12	21.32	5553.44	68.93	1642.34	14	28.74	632.71	4161.45	50.84
r109_21	2022.59	26	35.40	0.00	6535.40	16.81	1897.49	18	33.21	1347.62	5880.83	279.54	1908.28	23	33.40	0.00	5783.40	53.19	1865.06	18	32.63	1107.50	**5640.13**	110.62
r110_21	1453.34	8	25.43	11301.61	13327.05	17.10	1623.76	15	28.42	985.76	4764.18	293.66	1812.20	21	31.71	0.00	5281.71	75.50	1581.41	15	27.67	780.12	**4557.79**	140.53
r111_21	1464.14	8	25.62	10980.28	13005.90	17.05	1732.29	16	30.32	883.89	4914.21	269.98	1855.92	22	32.48	29.29	5561.77	68.08	1697.81	16	29.71	849.71	**4879.42**	92.17
r112_21	1464.14	8	25.62	8108.40	10134.02	16.83	1705.28	15	29.84	582.21	4362.05	286.21	1686.41	17	29.51	33.26	**4312.77**	55.02	1705.28	15	29.84	582.21	4362.05	61.70
r201_21	887.91	5	15.54	63015.96	64281.50	53.25	1400.90	10	24.52	0.00	2524.52	261.01	1211.94	7	21.21	0.14	1771.35	369.12	1142.86	7	20.00	1.27	**1771.27**	439.58
r202_21	834.00	5	14.60	54308.71	55573.31	56.62	1230.22	8	21.53	0.00	2021.53	284.89	1117.20	5	19.55	1.12	1270.67	493.34	1048.77	5	18.35	0.14	**1268.49**	485.02
r203_21	887.91	5	15.54	24859.55	26125.09	52.48	1152.98	9	20.18	0.00	2270.18	265.85	948.44	6	16.60	0.00	1516.60	282.42	913.68	6	15.98	0.00	**1515.98**	507.51
r204_21	833.55	5	14.59	17416.83	18681.42	55.24	978.24	5	17.12	0.00	1267.12	409.91	799.48	4	13.99	0.00	1013.99	546.40	783.23	4	13.70	0.00	**1013.70**	913.46
r205_21	857.82	5	15.01	46784.77	48049.78	54.74	1309.02	9	22.91	0.00	2272.91	262.20	1068.78	6	18.70	0.00	1518.70	391.48	1030.88	6	18.04	0.00	**1518.04**	368.11
r206_21	896.71	6	15.69	41539.95	43055.64	53.22	1296.87	8	22.70	230.78	2253.48	299.06	936.39	6	16.39	0.00	**1516.39**	430.67	1113.58	7	19.48	230.78	2000.26	419.55
r207_21	865.45	7	15.15	33608.64	35373.79	58.86	1053.46	5	18.44	0.00	1268.44	396.37	869.71	4	15.22	0.00	**1015.22**	590.11	869.89	4	15.22	0.00	1015.22	749.79
r208_21	837.41	9	14.66	27696.18	29960.83	52.96	955.63	6	16.72	0.00	1516.72	373.22	844.34	4	14.78	20.68	1035.46	247.54	774.77	4	13.55	0.00	**1013.55**	420.83
r209_21	896.71	5	15.69	45100.79	46366.48	52.48	1309.40	6	22.91	669.97	2192.88	379.77	1129.70	6	19.77	0.16	**1519.93**	277.55	1003.97	6	17.56	220.14	1737.70	394.74
r210_21	887.91	4	15.54	46385.16	47400.70	53.42	1270.10	8	22.23	0.00	2022.23	319.81	1084.00	6	18.97	0.00	1518.97	355.47	929.04	6	16.25	0.00	**1516.25**	708.05
r211_21	865.45	6	15.15	25280.20	26795.34	59.42	1041.90	5	18.23	38.43	1306.66	441.36	805.13	4	14.09	0.00	**1014.09**	800.75	821.57	4	14.37	0.00	1014.37	1334.23

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Table V
DETAILED COMPUTATIONAL RESULTS OF SA, GSSA, VNS, AND GSVNS FOR LARGE RC-TYPE INSTANCES

Instance	SA						GSSA						VNS						GSVNS					
	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU	Dist.	Veh.	Carb.	Tard.	Total	CPU
rc101_21	1729.64	9	30.27	14507.52	16787.79	14.94	2053.90	19	35.94	1353.40	6139.34	258.12	2946.50	29	51.56	137.60	7439.16	60.39	2048.26	18	35.84	1406.91	**5942.75**	98.05
rc102_21	1729.64	9	30.27	10716.62	12996.89	14.91	1853.52	15	32.44	1865.97	**5648.41**	264.96	2992.64	28	52.37	16.22	7068.59	63.93	1866.09	16	32.65	1749.21	5781.86	69.77
rc103_21	1729.64	9	30.27	7779.06	10059.33	14.78	1947.11	16	34.07	980.67	**5014.74**	260.66	2591.95	23	45.36	27.45	5822.81	64.62	1947.11	16	34.07	980.67	5014.74	48.02
rc104_21	1729.64	9	30.27	5772.16	8052.43	14.77	1768.29	14	30.95	629.62	4160.57	274.60	2322.35	20	40.64	0.00	5040.64	47.31	1768.29	14	30.94	629.62	**4160.56**	48.34
rc105_21	1729.64	9	30.27	12428.40	14708.67	14.71	2060.37	16	36.06	1827.77	5863.83	263.27	2820.46	27	49.36	35.18	6834.54	66.00	2060.37	16	36.05	1827.77	**5863.82**	48.87
rc106_21	1729.64	9	30.27	11854.00	14134.27	14.80	1978.18	17	34.62	959.02	5243.64	267.98	2745.77	26	48.05	84.31	6632.36	40.99	1935.75	17	33.87	847.90	**5131.77**	88.48
rc107_21	1729.64	9	30.27	8980.39	11260.66	14.88	1809.04	14	31.66	1084.42	4616.08	277.84	2237.10	20	39.15	15.26	5054.41	61.70	1809.04	14	31.65	1084.42	**4616.07**	65.97
rc108_21	1729.64	9	30.27	7482.84	9763.11	14.87	1986.39	15	34.76	483.22	**4267.98**	275.24	2166.44	19	37.91	54.85	4842.76	59.88	1986.39	15	34.76	483.22	4267.98	49.88
rc201_21	990.50	2	17.33	49232.06	49749.40	48.80	1666.92	13	29.17	0.06	3279.23	216.85	1357.47	8	23.76	0.00	**2023.76**	368.96	1332.77	8	23.32	1.63	2024.95	544.25
rc202_21	969.58	9	16.97	39787.21	42054.18	53.86	1437.14	9	25.15	0.00	2275.15	268.47	1210.23	6	21.18	0.80	**1521.98**	555.79	1182.62	6	20.69	3.13	1523.82	582.59
rc203_21	990.50	8	17.33	35581.44	37598.77	49.83	1275.48	8	22.32	0.00	2022.32	273.46	1027.19	6	17.98	0.00	**1517.98**	413.21	1034.30	6	18.10	0.00	1518.10	153.13
rc204_21	1054.76	6	18.46	28889.69	30408.15	48.04	1261.97	7	22.08	0.00	1772.08	337.58	933.63	7	16.34	0.00	1766.34	300.90	1148.72	6	20.10	0.00	**1520.10**	77.86
rc205_21	1025.38	7	17.94	44977.05	46744.99	49.40	1519.10	10	26.58	0.80	2527.38	248.80	1460.95	8	25.57	0.00	2025.57	229.54	1252.82	7	21.92	0.80	**1772.72**	170.49
rc206_21	981.66	4	17.18	37986.55	39003.73	51.17	1569.34	10	27.46	0.00	2527.46	248.49	1270.04	6	22.23	0.00	1522.23	442.84	1107.00	6	19.37	2.21	**1521.58**	168.96
rc207_21	988.07	5	17.29	33381.62	34648.91	49.73	1320.99	8	23.12	0.00	2023.12	299.07	1265.30	6	22.14	0.00	1522.14	302.34	1178.95	6	20.63	1.09	**1521.72**	446.60
rc208_21	1039.54	6	18.19	24366.44	25884.63	47.65	1282.75	6	22.45	282.67	1805.12	374.66	1471.60	5	25.75	0.00	1275.75	61.22	1256.14	6	21.98	282.67	**1804.65**	263.49

Table VI
PAIRWISE PERFORMANCE ANALYSIS OF GSVNS - VNS AND GSSA - SA

Compared setting	Metric	N	✓ Better	= Equal	× Worse	Mean Gap (%)	Std Gap (%)	Mean Δ	Avg. Improvement (%)
GSVNS vs VNS	Distance	76	66	0	10	-16.889	15.709	-311.240	20.424
	CostCarbon	76	66	0	10	-16.894	15.707	-5.447	20.429
	Vehicles	76	49	21	6	-19.518	21.251	-3.632	33.300
	TotalCost	76	63	1	13	-11.485	17.683	-517.809	16.876
GSSA vs SA	Distance	76	39	0	37	-1.719	31.226	-160.193	26.877
	CostCarbon	76	39	0	37	-1.720	31.228	-2.804	26.879
	Vehicles	76	35	11	30	17.510	83.198	-1.934	38.441
	TotalCost	76	75	0	1	-49.479	32.177	-11155.308	50.469

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