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Optimizing Load Utilization and Routing Efficiency in CVRP: Varying Vehicle Capacity Case in the Automotive Industry Closed-Loop Supply Chain

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Abstract

This study investigates the effects of different vehicle types on route optimization within the framework of the Capacitated Vehicle Routing Problem (CVRP), which is a widely recognized and extensively studied problem in the field of logistics and supply chain management. The primary objective of CVRP is to determine the most efficient routes for a fleet of vehicles with limited carrying capacities to deliver goods to a set of customers, while minimizing overall transportation costs and time. In this context, the study places particular emphasis on the role of vehicle characteristics—such as load capacity, average speed, and fuel efficiency—in shaping the overall performance of route planning. By incorporating various types of vehicles into the optimization model, the research explores how these parameters influence key performance indicators such as total travel time, fuel consumption, and operational cost. To achieve this, a series of simulations were conducted using multiple data sets that reflect real-world delivery scenarios. These simulations compared route outcomes based on different vehicle types and configurations. The findings reveal that the selection of vehicle types significantly impacts the efficiency of routing solutions. Specifically, the strategic use of vehicles with varying capacities and characteristics can lead to substantial improvements in delivery performance and cost-effectiveness. Overall, the study highlights the importance of vehicle heterogeneity in CVRP optimization and provides insights that can support decision-makers in designing more effective and sustainable logistics strategies.

Keywords
Capacitated VRP, Mathematical Modelling, Routing, Mixed-Integer Programming, Efficiency, Optimization.

1. Introduction
In today's highly competitive manufacturing environment, effective management of logistics and distribution strategies plays a pivotal role in reducing operational costs, optimizing resource utilization, and meeting service level expectations (Smith et al., 2020). Among the key challenges in logistics, the Capacitated Vehicle Routing Problem (CVRP) stands out as a classical optimization problem widely applied in supply chain management (Johnson & White, 2018). This problem becomes particularly relevant in closed-loop logistics systems, where manufacturers and suppliers work together to ensure the timely delivery of goods (Brown & Lee, 2019). The CVRP involves determining the optimal routes for a fleet of vehicles, considering factors such as vehicle capacity, travel distance, and customer demand (Miller et al., 2021).

The motivation behind this research is to investigate whether the simultaneous use of two vehicle types with different load capacities can lead to greater logistical efficiency compared to the traditional approach, which typically uses a single vehicle type. Specifically, the study explores two vehicle types: Vehicle Type 1 with a capacity of 1500 kg, and Vehicle Type 2 with a capacity of 2000 kg, to assess the potential benefits of employing a fleet with heterogeneous vehicle capacities in the logistics process (Nguyen & Zhang, 2022).

While the concept of vehicle heterogeneity has been widely discussed in the theoretical literature, the novelty of this study lies in applying these theoretical insights to real-world data. The data used in this research is derived from an actual supplier network of a selected automotive manufacturer, providing a more practical and applied perspective to the problem. Thus, the modeling process not only involves mathematical analysis but also incorporates real-world considerations, ensuring the relevance of the findings to industrial practices (Anderson & Clark, 2023).

The primary focus of the study is to evaluate the impact of vehicle diversity on logistics efficiency in a multidimensional way. Key performance indicators such as average load utilization and total route length are analyzed to determine how the use of vehicles with varying capacities influences overall system performance. Additionally, the research examines how the integration of a second vehicle type contributes to optimizing loading efficiency and route planning. By combining theoretical modeling with real-world field data, this study offers valuable insights for both academic research and practical applications in logistics management (Smith et al., 2020).

1.1 Objectives

This research aims to develop and compare CVRP models with single-type and two-type vehicle configurations in a closed-loop distribution system between suppliers and a manufacturing facility. The primary objective is to evaluate the impact of vehicle diversity on logistical performance, focusing on key metrics like average load utilization, total route length, and overall efficiency. The study analyzes the operational outcomes of different vehicle configurations and validates performance improvements using numerical and graphical results. The unique contribution of this research is the application of theoretical CVRP models within a real-world supply network, specifically for a large-scale automotive manufacturer. Using empirical data, the study assesses how vehicle diversity affects routing efficiency and provides strategic recommendations for industrial stakeholders. The findings offer valuable insights for both academic literature and practical decision-making in supply chain management.

2. Literature Review

The Vehicle Routing Problem with Time Windows (VRPTW) and capacity constraints is a crucial optimization problem in logistics, particularly for operations following a Just-in-Time (JIT) delivery model. Exact optimization techniques like Mixed-Integer Programming (MIP), when solved using commercial solvers such as IBM ILOG CPLEX or GAMS, offer mathematically optimal solutions under well-defined constraints. Although VRPTW is NP-hard and exact methods are generally limited to small- or medium-sized instances, many studies have proposed MIP formulations that successfully solve real-world-sized problems or generate benchmark solutions for validation purposes.

2.1 Classical and Multi-Objective VRPTW

Solomon (1987) introduced benchmark datasets for VRPTW that remain widely used for validation. Aggarwal and Kumar (2019) developed a standard VRPTW model, minimizing transportation cost and vehicle usage. Their study highlighted how service time windows and load balancing influence route efficiency and fleet utilization. Mandal et al. (2024) enhanced classical VRPTW by introducing a compact MIP formulation with a discretization algorithm that refines the feasible space iteratively. This approach showed improved performance in terms of LP relaxation, tightness and scalability. Eydi and Ghasemi-Nezhad (2021) proposed a bi-objective VRPTW model—minimizing cost while maximizing customer satisfaction. Their work emphasized the trade-offs between total distance and service level, introducing demand prioritization as an optimization parameter. Ghoseiri et al. (2010) similarly adopted a multi-objective perspective by minimizing both total distance and customer wait times. Their implementation validated that customer-centric metrics can be integrated into exact models effectively.

2.2 VRPTW under Operational and Environmental Constraints

Dhahri et al. (2016) introduced a VRPTW with preventive maintenance constraints (VRPTW-PM). Their model included route duration limitations and maintenance scheduling, reflecting more realistic fleet operation scenarios. Agra et al. (2013) addressed travel time uncertainty through robust optimization, solving their two-index flow MIP model. They proved that uncertainty-aware models significantly alter route decisions under time-sensitive constraints. Pureza et al. (2012) modeled a VRPTW involving multiple delivery personnel per vehicle to reduce service time. A mathematical model and metaheuristics (Tabu Search and Ant Colony Optimization) are proposed and tested on benchmark instances to minimize total costs. Their deterministic equivalent model enabled robust planning for complex urban delivery settings. Mahjoob et al. (2021) presented a Green multi-period VRPTW model that minimized carbon emissions while satisfying time windows and capacity constraints. This multi-criteria bi-objective MIP is aligned with sustainability goals and transportation efficiency. Erdoğan and Miller-Hooks (2012) introduced the Green VRP with alternative-fuel vehicles and range-based refueling constraints. Their solution for small instances laid the groundwork for further studies in electric vehicle routing optimization.

2.3 Multi-Trip and Multi-Depot VRPTW
Fermín-Cueto et al. (2021) studied a multi-trip VRPTW including fleet sizing and depot location decisions. Their MIP model was solved by a branch-and-cut procedure, demonstrating effective integration of strategic planning into daily routing. Zhen et al. (2020) tackled a multi-depot, multi-trip VRPTW with customer release dates. Their model was implemented and validated through exact solutions for medium-sized datasets, proving the feasibility of solving more complex logistics scenarios via MIP.

2.4 Simultaneous Pickup and Delivery
Angelelli and Mansini (2002) developed a set-partitioning MIP formulation for the VRP with Simultaneous Pickup and Delivery and Time Windows (VRPSPD-TW), solved using the branch-and-bound algorithm. Their work solved instances of up to 50 customers and demonstrated exact solvability with route-based modeling. Wang et al. (2016) investigate a multiobjective VRPSDPTW, introducing realistic instances with five objectives. They compare two algorithms—multiobjective local search (MOLS) and multiobjective memetic algorithm (MOMA)—and find that MOLS generally performs better, although its advantage is less pronounced in real-world scenarios. Zhang et al. (2024) address the challenges of rural e-commerce logistics in China by proposing a cooperative vehicle routing model for simultaneous pickup and delivery, incorporating home delivery and self-pickup options. Using a tailored optimization algorithm and cost-sharing mechanism, the model significantly reduces operational costs across varying demand levels and network structures..

2.5 Synthesis and Research Gaps
Existing studies highlight the strengths and limitations of exact MIP formulations for the Vehicle Routing Problem with Time Windows (VRPTW). While solvers like CPLEX and GAMS can deliver optimal solutions for problem sizes with up to 50–100 customers, large-scale or highly constrained cases often demand hybridization or decomposition approaches. A significant research gap lies in the limited integration of Just-In-Time (JIT) manufacturing requirements into VRPTW models. Moreover, few studies explore depot-originating vehicle flows in supplier-to-factory logistics, particularly in automotive production contexts.

The present study makes a prominent contribution by addressing these gaps directly. It develops and models a depot-initiated, multi-vehicle VRPTW, incorporating both capacity and time constraints using GAMS. The model is specifically aligned with the operational realities of JIT supply chains in the automotive industry, offering new insights into optimizing logistics within this context. This research not only bridges these gaps but also introduces a practical, real-world application of VRPTW in a critical industry setting.

3. Modelling
This study formulates the Capacitated Vehicle Routing Problem (CVRP) as a Mixed-Integer Programming (MIP), which is the fundamental optimization problem in Logistics. The model utilizes GAMS to address the problem of optimizing routes for a fleet of vehicles tasked with serving a predetermined set of customers, each with specific demands. The vehicles begin and end their journeys at a central depot, and they are subject to limitations in both capacity and maximum allowable travel distance. The study is based on a real-life industrial case from the automotive sector. In the examined scenario, vehicles depart from the manufacturer's facility, visit designated suppliers to collect materials, and then return to the same production site. The model is formally structured using the following components:

Model Structure
Sets:

- *N*: Set of nodes (customers and depot)
- *K*: Set of vehicles

Parameters:

- d_{ij}*: Distance between node i and node j*
- b_i*: Demand of customer i*
- a_k*: Capacity of vehicle k*
- $maxDistance_k$*: Maximum distance vehicle k can travel*
- *c: Unit transportation cost per distance*

Decision Variables:

- $x_{ijk} = \begin{cases} 1, if\ vehicle\ k\ travels\ from\ node\ i\ to\ node\ j \\ 0, otherwise \end{cases}$
- $y_{ijk} = \begin{cases} 1, if\ vehicle\ k\ serves\ node\ i \\ 0, otherwise \end{cases}$
- $u_{ik} = Subtour\ elimination\ variable\ for\ customer\ i\ and\ vehicle\ k$
- $Z_{ijk} = Total\ transportation \cos(objective\ function)$

Objective Function

Minimize total transportation cost:

$$\boldsymbol{Z = c \times \sum_i \sum_j \sum_k d_{ij} \times x_{ijk}} \tag{1}$$

The function to minimize (eq. 1) is subject to the following constraints:

Constraints

Vehicle Capacity Constraint:

$$\sum_i b_i \times y_{ik} \leq a_k,\ \forall\ k\ \in\ K \tag{2}$$

Depot Assignment Constraint:

$$\sum_k y_{depot,k} = |K| \tag{3}$$

Customer Assignment Constraint:

$$\sum_k y_{ik} = 1,\ \forall\ i\ \in\ N,\ i\ \neq\ depot \tag{4}$$

Flow Conservation Constraint:

$$\sum_j x_{ijk} = y_{ik},\ \forall\ i\ \in\ N,\ \forall\ k\ \in\ K \tag{5}$$

Maximum Travel Distance Constraint:

$$\Sigma_{\mathrm{i}}\, \Sigma_{\mathrm{j}}\, d_{\mathrm{ij}} \times x_{\mathrm{ijk}} \leq maxDistance_{\mathrm{k}} \qquad \forall\ k\ \in\ K \tag{6}$$

Subtour Elimination Constraints:

$$u_{ik} - u_{jk} + a_k \times x_{ijk} \leq a_k - b_j,\ \forall\ i,j\ \in\ N \setminus \{depot\}, i\ \neq\ j, b_{\mathrm{i}} + b_{\mathrm{j}} \leq a_{\mathrm{k}} \tag{7}$$

Bounds on Sub-tour Variable:

$$b_i \leq u_{ik} \leq a_k, \forall\ i\ \in\ N \setminus \{depot\}, \forall\ k\ \in\ K \tag{8}$$

$$x_{ijk} \in \{0,1\}, y_{ijk} \in \{0,1\} \tag{9}$$

The objective function represented in **Equation (1)** aims to **minimize the total transportation cost**, which is computed as the product of the distance travelled between nodes and a fixed unit transportation cost coefficient. This objective reflects the goal of achieving cost-efficient routing solutions within the distribution network.

Equation (2) imposes the **vehicle capacity constraint**, which ensures that the total customer demand allocated to each vehicle does not exceed its respective capacity. This condition is essential for maintaining the feasibility of the routes with respect to the physical limitations of the fleet.

Equation (3) enforces the **depot assignment constraint**, stipulating that each vehicle must be routed from the depot. This guarantees that all vehicles begin their tours from a central location and supports the operational integrity of the routing process.

Equation (4) addresses the **customer assignment requirement**, ensuring that each customer is visited exactly once by a single vehicle. This constraint prevents multiple servicing of the same customer and guarantees a unique allocation in the solution.

Equation (5) ensures **flow conservation** by establishing that if a vehicle is assigned to a customer, it must both arrive at and depart from the customer's location. This maintains the continuity and integrity of the vehicle's tour.

Equation (6) introduces the **maximum travel distance constraint**, which restricts the total distance traversed by each vehicle to remain within a predefined limit. This models practical considerations such as fuel capacity, regulatory driving hours, or other operational constraints.

Equation (7) represents the **sub-tour elimination constraint**, formulated using the Miller–Tucker–Zemlin (MTZ) approach. It eliminates the possibility of isolated cycles that do not include the depot, thereby preserving the coherence of each route.

Equation (8) provides **bounds on the sub-tour elimination variable** u_{ik}, ensuring that it remains within valid limits. These bounds are critical to the proper functioning of the MTZ formulation and contribute to the effectiveness of the sub-tour elimination strategy. Finally, Equation (9) shows the binary variables used in the proposed model.

4. Data Collection

In this study, actual data were collected in order to design and evaluate a CVRP instance under controlled conditions. The dataset was generated to reflect the key components of a real-world distribution system, including customers, vehicles, demands, and distances. The distribution network consists of one central depot and ten customer nodes, labeled K1 through K18. Each customer node is associated with a specific demand value, ranging from 150 to 875 units, while the depot has no demand. These demand values were assigned randomly within a realistic range to simulate heterogeneity in customer requirements. The distance matrix, defined symmetrically for all node pairs (including the depot), was constructed to represent plausible travel distances in a medium-scale geographic region. These values were manually designed to ensure diversity in routing choices and to allow the model to explore alternative paths. The fleet comprises four vehicles (T1 to T8), with two different capacity levels: 1500 units for T1 and T2, and 2000 units for T3 and T4. To incorporate operational limitations, each vehicle was also assigned a maximum travel distance constraint of 50 units. This constraint simulates practical considerations such as fuel capacity or driver working hours. A fixed transportation cost coefficient (c = 8.5) was employed to convert total travel distance into monetary cost, forming the basis of the model's objective function. The use of synthetic data facilitates flexibility in modeling and ensures replicability of the experimental results. Moreover, it enables the examination of model behavior under different parameter configurations without dependency on proprietary or location-specific datasets.

Table 1 presents the configuration of customer and vehicle allocations across multiple problem instances designed to evaluate the performance of the Capacitated Vehicle Routing Problem (CVRP) model under varying scales. The table categorizes the instances into four groups based on the problem size: Very Small Scale, Small Scale, Medium Scale, and Large Scale.

Each instance is defined by the number of customers to be served and the number of vehicles available for dispatch. The progression of instances reflects incremental increases in complexity. The Very Small-Scale group includes instances with 5 and 6 customers, served by 2 vehicles. The Small-Scale group expands to 8 and 10 customers, requiring 4 vehicles. The Medium Scale scenarios involve 12 and 14 customers, supported by 6 vehicles. Finally, the Large-Scale group comprises instances with 16 and 18 customers, with routing responsibilities distributed across 8 vehicles (Table 1)

Table 1. Customer and Vehicle Allocation for Different Problem Sizes

Instance Description	Number of Customers	Number of Vehicles
Very Small-Scale 1	5	2
Very Small-Scale 2	6	2
Small Scale 1	8	4
Small Scale 2	10	4
Medium Scale 1	12	6
Medium Scale 2	14	6
Large Scale 1	16	8
Large Scale 2	18	8

5. Results and Discussion

5.1 Numerical Results

The total cost results obtained from solving the CVRP using both single-type and two-type vehicle configurations across various problem instances. The data indicates that using two types of vehicles consistently reduces the total routing cost. For instance, in the Very Small Scale 2 instance, the cost decreased from 408 to 332 units, resulting in a 19% reduction. Similarly, for Small Scale 2, a 13% reduction was observed (Table 2).

Table 2. Comparison Matrix for CVRP with Single Type vs. Two Types of Vehicles

Instance Description	# of Customers	Vehicle Configuration	Average Load Utilization	Average Route Length	Solution Quality (in terms of Load Utilization)	Solution Quality (in terms of Road Length)
Very Small-Scale 1	5	Single Type	505	2037.5	0%	1%
Very Small-Scale 1	5	Two Types	505	2050		
Very Small-Scale 1	6	Single Type	495.8333333	2775	0%	20%
Very Small-Scale 1	6	Two Types	495.8333333	3478.5		
Small Scale 1	8	Single Type	484.375	1518.75	0%	14%
Small Scale 1	8	Two Types	484.375	1775		
Small Scale 1	10	Single Type	456.55	2053.25	3%	20%
Small Scale 1	10	Two Types	470.9	2573.75		
Medium Scale 1	12	Single Type	469.9166667	1760.833333	0%	1%
Medium Scale 1	12	Two Types	469.9166667	1780.333333		
Medium Scale 1	14	Single Type	472.7857143	2077.333333	0%	20%
Medium Scale 1	14	Two Types	472.7857143	2585.666667		
Large Scale 1	16	Single Type	467.75	1864.375	0%	0.06%
Large Scale 1	16	Two Types	467.75	1865.5		
Large Scale 1	18	Single Type	466.6111111	1902.5	0%	49%
Large Scale 1	18	Two Types	466.6111111	969.6666667		

Operational performance indicators, such as average load utilization, average route length, total route length, and total load, are given in Table 2. While the average load utilization remains mostly stable across both configurations, the average and total route lengths tend to be shorter in two-type configurations in larger-scale instances, suggesting more efficient route distribution.

The numerical results indicate that incorporating vehicle heterogeneity enhances routing performance in terms of cost and operational efficiency. The improvement is more pronounced in small to medium-sized instances, while larger instances still benefit to a lesser degree.

5.2 Graphical Results

Figure 1 illustrates the cost reduction percentages relative to the number of customers. Although the trend exhibits slight fluctuations, smaller-scale instances generally show higher improvement rates. This reflects the greater flexibility and efficiency gains achievable when more varied vehicle types are available in compact networks.

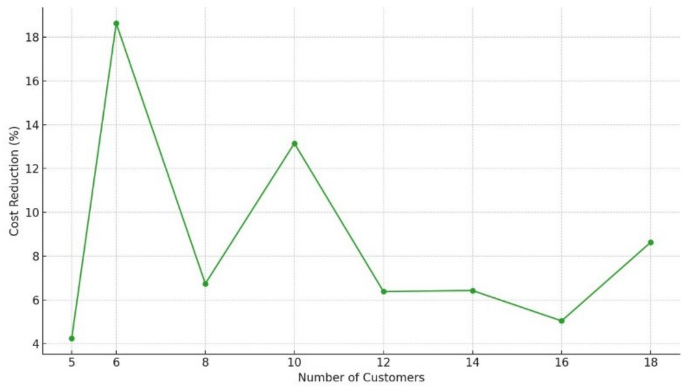

Figure 1. Solution Quality (Cost Reduction) vs Number of Customers

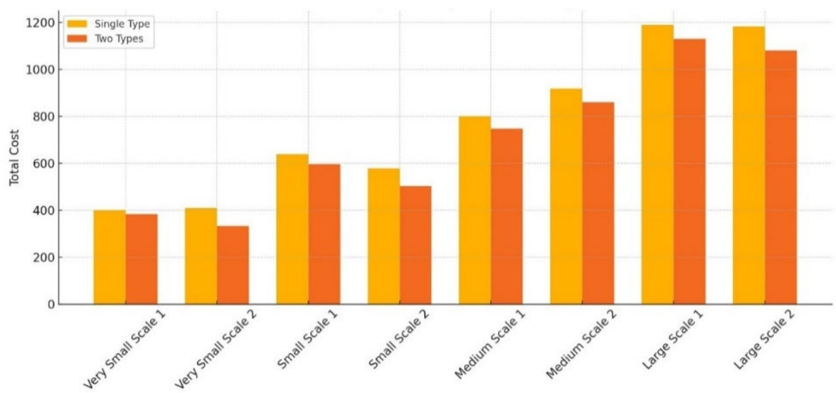

Figure 2. Total Cost Comparison by Vehicle Configuration

Comparison of the total cost for each instance under both configurations can be seen in Figure 2. Across all problem sizes, the two-type vehicle configuration consistently results in lower total cost, supporting the conclusion that diversified fleets are advantageous. Visual analysis supports the numerical findings and strengthens the argument for multi-type vehicle integration in CVRP solutions. The Pareto analysis is particularly useful for prioritizing future modeling or heuristic enhancements based on observed impact.

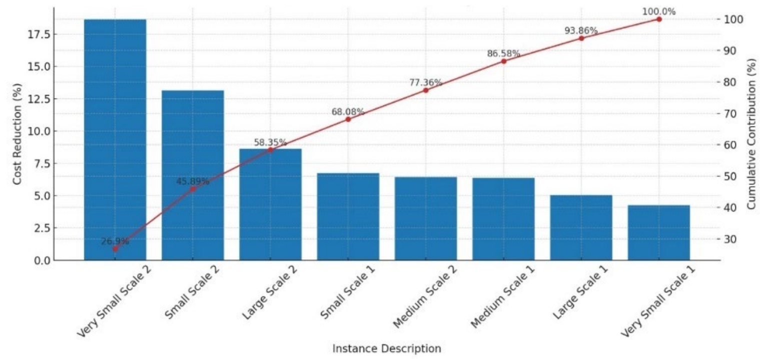

Figure 3. Pareto Chart of Cost Reduction by Instance

Figure 3 presents a Pareto chart ranking the problem instances by their contribution to overall cost savings. The top three contributors (*Very Small Scale 2*, *Small Scale 2*, and *Large Scale 2*) collectively account for more than 58% of the total reduction. This distribution highlights which instances benefit most from vehicle type variation and can guide future optimization focus. The line in the Pareto chart represents the **cumulative contribution** of cost reduction across instances. It shows how the total cost reduction builds up as you move from the most impactful instances to the least. The purpose of the line is to highlight the most significant contributors to cost reduction, in line with the Pareto principle, which suggests focusing on the few instances that yield the largest impact.

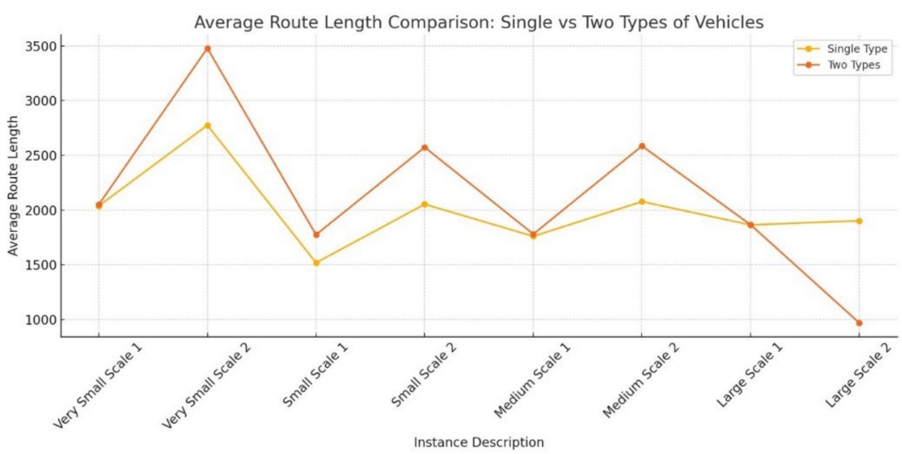

Figure 4. Average Route Length Comparison: Single vs Two Vehicles

Comparison of average route lengths across different instance sizes when using single-type versus two-type vehicle configurations is presented in Figure 4. A general observation is that route lengths vary considerably across instances, with certain instances showing significant differences between configurations. For instance, in *Very Small Scale 2*, the average route length increases significantly when switching to a two-type configuration. This can be attributed to the distribution of customer demands and the usage of smaller-capacity vehicles, which may increase the number of required sub-routes. However, in *Large Scale 2*, the average route length under the two-type configuration is nearly halved compared to the single-type case, indicating substantial efficiency gains in larger networks.

The results highlight that the effectiveness of heterogeneous vehicle configurations on route length is not uniform across instances. While small-scale instances may occasionally show increased route lengths due to additional vehicle variety, large-scale instances tend to benefit significantly from optimized route structures. This suggests that vehicle heterogeneity enhances routing flexibility, particularly in complex distribution scenarios.

5.3 Proposed Improvements

Based on the findings of this study, several potential enhancements to the current solution approach are proposed. First, integrating adaptive algorithms that dynamically select vehicle types based on customer distribution and demand density could significantly improve system responsiveness and efficiency. Additionally, the model could be extended to incorporate further constraints such as time windows or specific service level requirements, making it more applicable to real-world scenarios. Another improvement involves the use of multi-objective optimization techniques to simultaneously balance cost, load utilization, and total route length. Furthermore, performing sensitivity analyses by varying vehicle capacities, customer demands, and fleet compositions would provide deeper insights into the model's robustness and adaptability. Lastly, benchmarking the model's performance against established metaheuristic or exact methods in the literature would help evaluate the quality of the solutions and the computational efficiency of the proposed approach.

5.4 Validation

To assess whether the cost improvements observed by using two-type vehicle configurations are statistically significant, formal validation through inferential statistics is required. A suitable approach in this context is the use of a paired-sample t-test, which compares the total costs of the same problem instances solved under two different configurations: single-type and two-type.
This test is appropriate because:

- The same problem instances (with identical demand, geography, and customer numbers) are used in both cases, ensuring that each pair of values is dependent.
- The aim is to determine whether the difference in total cost between configurations is statistically significant rather than due to random variation.

Hypothesis Testing Framework:

- Null Hypothesis (H_0): There is no statistically significant difference between the mean total costs of single-type and two-type vehicle configurations.

$$\boldsymbol{H_0 = \mu_{single} = \mu_{two}}$$

- Alternative Hypothesis (H_1): The mean total cost for the two-type vehicle configuration is significantly lower than that for the single-type configuration.

$$\boldsymbol{H_1 = \mu_{single} > \mu_{two}}$$

This is a one-tailed test since the expectation is directional (lower cost with two-type configuration).
Procedure:

1. Compute the pairwise differences in total cost between the configurations for all instances.
2. Calculate the mean and standard deviation of these differences.
3. Use the t-distribution to calculate the t-statistic and p-value.
4. Compare the p-value to a significance threshold (commonly $\alpha = 0.05$).

Paired-Sample t-Test Procedure

To assess the statistical significance of the difference in total route lengths between the two configurations, we calculated the pairwise differences for each instance. The difference for each instance was calculated as:

Difference_i = Total Route Length $(Two\ Types)_i$ - Total Route Length $(Single\ Types)_i$

Differences = [25,1407,1025,2082,117,3050,9,2234]

Mean of the differences (μ)

The mean of the differences was computed as the sum of the differences divided by the number of instances (n=8):

$$\mu = \frac{1}{n}\sum_{i=1}^{n} Difference_i = \frac{25+1407+1025+2082+117+3050+9+2234}{8} = 1243.63$$

Standard deviation of the differences

$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Difference_i - \mu)^2}$

Differences from mean = [−1218.63,163.37,−218.63,838.37,−1126.63,1806.37,−1234.63,990.37]

Squared differences = [1485406.5,26690.3,47832.7,702655.2,1267867.8,3261312.2,1525414.6,980836.1]

The sum of the squared differences is: 11526215.4

$\text{Variance} = \frac{Sum\ of\ squares}{n-1} = \frac{11526215.4}{7} = 1646802.2$

Standard Deviation is:

$\sigma = \sqrt{1646802.2} = 1152.63$

t-Statistic and p-Value Calculation

$t = \frac{\mu}{\frac{\sigma}{\sqrt{n}}} = \frac{1243.63}{\frac{1152.63}{\sqrt{8}}} = 3.05$

The p-value was computed using the t-distribution with n−1=**7** degrees of freedom. For this one-tailed test, the p-value is **0.0093.**

Since the p-value is less than the significance threshold of 0.05, the null hypothesis is rejected. This implies that the observed cost reductions from using two vehicle types are statistically significant and not due to random chance. A one-tailed paired-sample t-test was performed with a significance level of $\alpha=0.05$. The test yielded a t-statistic of 3.05, and a corresponding p-value of 0.0093. Given that the p-value is less than 0.05, we can confidently reject the null hypothesis and conclude that the two-type vehicle configuration results in a statistically significant reduction in total route length compared to the single-type configuration.

Although visual analysis and individual comparisons suggested that two-type configurations generally provide better routing solutions, the statistical test provides conclusive evidence that the improvement observed is indeed statistically significant across all instances, rather than being attributed to random variation.

This result underscores the potential of using heterogeneous vehicle fleets in optimizing vehicle routing. By applying statistical hypothesis testing, the observed cost advantages of using two vehicle types are validated with scientific rigor. This step is crucial for translating empirical observations into generalizable conclusions that are applicable to broader classes of CVRP instances.

6. Conclusion

The results clearly indicate that using a mixed fleet with heterogeneous vehicle types leads to notable improvements in key logistics performance metrics. Specifically, configurations that include vehicles with different load capacities achieved higher load utilization rates, reduced total travel distances, and improved cost efficiency compared to single-vehicle-type scenarios.

These outcomes demonstrate that vehicle diversity enhances the system's ability to adapt to varying customer demands and geographical constraints. By better aligning vehicle capacities with delivery requirements, routing efficiency is significantly improved, enabling more effective resource allocation and lower operational costs.

The results also underscore the practicality of applying CVRP models to real-world-inspired data, reflecting the dynamics of an actual supply network. This alignment between theoretical modeling and practical application offers valuable support for logistics decision-making in industrial contexts.

Further gains could be achieved by integrating adaptive algorithms, adding constraints such as time windows, or employing multi-objective optimization techniques. These extensions would contribute to a more comprehensive and realistic approach, increasing the robustness and scalability of routing solutions in complex distribution systems.

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Biographies

Mertcan Karakaya is an Industrial Engineering undergraduate at Çankaya University, with a focus on supply chain management, production systems, and logistics. He is currently working on his graduation project at MAN Türkiye A.Ş., conducting field-based and analytical research to enhance supply chain efficiency through data-driven methods. In 2024, he completed a procurement internship at Viking Services, gaining experience in supply management and Excel-based reporting tools. He also interned at Akdaş Döküm in 2022, contributing to reporting and R&D efforts. Motivated and forward-thinking, Mertcan aims to optimize operations using data-driven strategies and innovative technologies, striving to deliver sustainable and scalable solutions in dynamic business environments.

Aybüke Sözer is a senior Industrial Engineering student at Çankaya University. Her academic interests include logistics optimization, data analysis, and simulation modeling. She has conducted a senior project with MAN TR, focusing on logistics process improvement using the milk-run method. She completed a long-term internship at Savronik, where she worked on UI development, data transfer, and project reporting. Proficient in tools such as Power BI, Python, and ARENA Simulation, she combines engineering knowledge with software skills. She speaks English fluently and has basic proficiency in German and French.

Canberk Tuğcu is a senior Industrial Engineering student at Çankaya University, with a focus on project management, procurement, production planning, and business development. He has completed internships at RMK Marine, Ernst & Young, MILSOFT, and TEPE Home, gaining hands-on experience in strategic planning, consulting, software project management, and sales. Canberk aims to pursue a career in project management and business development. Outside of academics, he is also a semi-professional composer and guitarist.

İrem Görmez started her Industrial Engineering studies at Çankaya University in 2019 and is expected to graduate in 2025. She is also a third-year Business Administration student at Anadolu University, which she began in 2022. Her main academic interests are in supply chain management and production planning, and she is focused on gaining both theoretical knowledge and practical experience in these fields.
She is an active member of the IEEE Çankaya University Student Branch Education Unit and has completed various internships at companies such as FNSS, TAI (Turkish Aerospace Industries), Arca Software, STM, and Nurol Technology. Currently, she is working on her graduation project in supply chain and logistics at MAN Turkey (2024–2025), while also interning in Composite Production Planning at TAI. Her goal is to specialize in supply chain management and production planning and to develop innovative solutions in these areas.

Syed Shah Sultan Mohiuddin Qadri is an Assistant Professor in the Department of Industrial Engineering at Çankaya University, Ankara, Türkiye. He holds a Ph.D. in Industrial Engineering from Yasar University, Izmir, Türkiye. Dr. Qadri earned his BS and MS degrees in Applied Mathematics from the University of Karachi and NED University of Engineering & Technology, Karachi, Pakistan, in 2010 and 2013, respectively. He has worked as a researcher on a TÜBİTAK-funded project, and his research interests include simulation optimization, intelligent transportation systems, heuristic optimization, and traffic modeling. Dr. Qadri is dedicated to advancing optimization techniques for solving complex real-world problems.

Cihan Kaan Güngördü is an undergraduate student in Industrial Engineering at Çankaya University. He holds certifications in Supply Chain Operations, Inventory Management, and Financial Accounting from institutions like Rutgers and UC Irvine. His academic interests include lean manufacturing, operations research, and process optimization. He has hands-on experience with ERP systems such as SAP and IFS and has worked at Bozankaya and several other companies in logistics, supplier evaluation, and production. Currently, he is conducting a logistics efficiency project at MAN Türkiye. He plans to pursue graduate studies with a focus on research and data-driven decision-making.