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Multi-Depot Vehicle Routing Problems: A Narrative Review of Problem Variants, Algorithms, and Benchmarking Practices (2021–2026)

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Abstract

Over the past few years, the Multi-Depot Vehicle Routing Problem (MDVRP) has become a widely studied optimization problem in transportation and logistics. It models real-world distribution systems in which fleets of vehicles are deployed from multiple depots to serve a shared customer base while satisfying increasingly stringent operational constraints, including vehicle capacities, customer time windows, route durations, and environmental considerations. This review systematically analyzes 100 studies on the Multi-Depot Vehicle Routing Problem (MDVRP) published between 2021 and 2026 to provide a comprehensive understanding of problem variants, solution methodologies, and benchmarking practices. Our results indicate a steady enrichment of the literature: time windows are considered in most studies (59%), electric and green routing have grown markedly, and collaboration, fleet heterogeneity, and dynamic operation appear ever more frequently. Metaheuristics remain the methodological core (83%). Still, they are increasingly embedded in hybrid and learning-augmented frameworks, while learning-based methods (17%), including reinforcement learning, graph neural networks, and transformers, have concentrated in recent years. Exact methods (30%) persist, chiefly as components within decomposition schemes. Benchmarking practice is uneven: Cordeau's instances remain the most common shared reference, yet classical instances are used in fewer than half of the studies, and modified, synthetic, and largely unreleased real-world datasets fill the frontier.

1. Introduction

The Vehicle Routing Problem (VRP) is a fundamental combinatorial optimization challenge central to logistics, transportation, and supply chain management.(Pangaribuan et al., 2025). The process determines the most efficient delivery routes for a fleet of vehicles serving multiple customer locations. Specifically, it involves identifying the optimal sequence for multiple vehicles to visit various delivery points in order to minimize costs while adhering to operational constraints. (Tsuyumine et al., 2024).

The Multi Depot Vehicle Routing Problem, or MDVRP, differs from the classical VRP primarily in that it considers multiple depots rather than a single depot. Multiple sources consistently characterize MDVRP as a generalization or extension of VRP. The Multi-Depot Vehicle Routing Problem (MDVRP) extends the classical VRP by considering multiple depots, from which vehicles depart and to which they return while collectively serving a set of customers (Carlsson et al., 2007; Kaur, 2013). MDVRP is also considered an important variant of the classical Vehicle Routing Problem (VRP), in which customers can be served from multiple depots.

In the classical Vehicle Routing Problem (VRP), all vehicles operate from a single depot. However, the Multi-Depot Vehicle Routing Problem (MDVRP) extends this assumption by considering multiple depots, making it a more realistic representation of real-world distribution systems. As noted by Jayarathna et al. (2020), the MDVRP is "a more realistic version of the classical VRP, where the distribution of goods is done from several depots" (Jayarathna et al., 2020) This extension introduces a fundamental additional decision: assigning customers to depots before optimizing vehicle routes. The importance of this

assignment process is further emphasized by Juan et al. (2015), who proposed a biased randomization strategy to assign customers to depots according to a randomized priority criterion before constructing vehicle routes. (Juan et al., 2015).

Customer-to-depot assignment significantly increases the complexity of the MDVRP. Unlike the classical VRP, the MDVRP requires simultaneous consideration of two tightly coupled decision processes: assigning customers to depots and designing vehicle routes. These decisions are highly interdependent, as the assignment of customers to depots determines the set of available vehicles, influences which customers can be grouped into the same route, and ultimately affects the total travel distance and operational cost. Consequently, changes in customer-to-depot allocation directly alter the routing solution, substantially enlarging the search space and making the optimization problem considerably more challenging (Calvet et al., 2016).

The interdependence between depot assignment and route construction has important implications for solution methodology. The quality of routing solutions depends on the assignment strategy, whereas the effectiveness of customer assignments depends on the spatial distribution of customers and depots. (Tansini et al., 2001), Zhang et al. (2007) highlighted this challenge by decomposing the integrated MDVRP model into smaller subproblems to overcome the computational difficulty associated with its high-dimensional mathematical formulation. In practical applications, customer-to-depot assignments cannot be determined independently of routing decisions. A depot that appears optimal for an individual customer may produce inefficient customer clusters, violate vehicle capacity or fleet availability constraints, or result in significantly longer routes. Consequently, decomposition-based approaches, particularly cluster-first, route-second heuristics and hybrid optimization frameworks, remain widely adopted to solve the MDVRP rather than directly solving the integrated mathematical formulation.

The MDVRP is classified as NP-hard because it is a complex combinatorial problem that generalizes the Traveling Salesman Problem (TSP). As the number of customers and depots increases, the number of possible routing and vehicle combinations grows at a factorial rate, making it computationally infeasible to find an optimal solution via brute force (Pintarič & Karakatič, 2019).

Three developments have driven the recent interest in the MDVRP. First, decentralized last-mile and quick commerce logistics have made multiple depots the norm rather than the exception. (Choi et al., 2026; Tavana et al., 2026) (Campuzano et al., 2025) Another major challenge arises from the increasing complexity of real-world logistics operations. Contemporary distribution systems are subject to numerous operational constraints, such as customer time windows, battery capacity and charging requirements for electric vehicles, driver working-hour regulations, temperature-controlled transportation, and the coordination of ground vehicles with drones or other autonomous delivery systems. As a result, the classical capacity-constrained Multi-Depot Vehicle Routing Problem (MDVRP) constitutes a simplified special case and does not accurately represent the complexities of modern distribution networks. (Y. Liu et al., 2026; Nozari & Yordanova, 2026; Y. Wang et al., 2026). The third challenge concerns the rapid evolution of solution methodologies. While metaheuristic algorithms remain

prevalent in MDVRP research, there has been a notable increase in the adoption of hybrid optimization frameworks and learning-based approaches in recent years. These methods have significantly expanded the range of algorithms available for addressing increasingly complex and large-scale MDVRP variants. (H. Liu et al., 2026; Wu et al., 2026) (Movahedkor et al., 2026) .

The objective of this review is to examine the MDVRP literature published between 2021 and 2026 and to characterize recent developments in the field. Specifically, the review analyzes the evolution of problem variants, solution methodologies, and benchmarking practices. Rather than following a formal systematic review protocol, this study presents a narrative synthesis that identifies major developments and research trends across approximately one hundred published studies. The objective is not to provide an exhaustive assessment of the literature or a formal identification of research gaps, but rather to synthesize the principal directions of recent research. Section 2 describes the scope of the review, and Section 3 presents a taxonomy of MDVRP variants. Sections 4–8 examine problem variants, solution methodologies, benchmarking practices, operational constraints, and optimization objectives, respectively. Section 9 discusses the principal findings, and Section 10 concludes the review.

2. Scope and Method

This review covers 100 MDVRP studies published between 2021 and 2026. Each study was classified across twelve dimensions: publication year, problem variant, solution approach, algorithm, objective(s), constraints, depot and fleet characteristics, benchmark instances, benchmark category, and principal contribution. Figure 1 illustrates the distribution of the reviewed studies by publication year, from 2021 to 2026. Appendix Table A1 summarizes the reviewed studies by publication year, problem variant, solution methodology, key constraints, optimization objectives, application sector, benchmark dataset, and principal contribution.

3. Taxonomy of MDVRP Research

The reviewed literature supports a taxonomy of variant classes, which we organize into three families. Structural variants alter the network or the routing topology; they include the classical MDVRP, the multi-depot open VRP, location-routing, two-echelon, periodic, and multi-trip, and arc-routing formulations. Feature-rich variants add operational features to the vehicles or the environment, namely electric fleets, green objectives, drone or UAV assistance, cold-chain constraints, and dynamic, stochastic, or time-dependent conditions. Objective-driven variants reshape the goal or the cooperation structure and comprise collaborative, pickup-and-delivery, split-delivery, heterogeneous-fleet, multi-objective, and profit-fairness formulations. The classical MDVRP now appears chiefly as an algorithmic baseline (Stodola & Nohel, 2023; Wan et al., 2023), whereas the feature-rich and objective-driven families define most of the current work (Y. Liu et al., 2026; Y. Wang et al., 2026) (Y. Wang et al., 2025)(Q. Zhang et al., 2022). The proposed taxonomy is intentionally non-partitional, reflecting that modern MDVRP variants frequently combine multiple characteristics rather than belong to a single category. As discussed in the following sections, these problem classes are often integrated to model increasingly complex real-world logistics

scenarios. Figure 2 illustrates the taxonomy as a three-branch hierarchical tree rooted in the classical MDVRP.

4. Problem Variants

Time-window constraints have become a fundamental component of contemporary MDVRP formulations, reflecting the increasing emphasis on service reliability and customer-oriented logistics. Their widespread adoption across diverse application domains, including quick-commerce delivery (Tavana et al., 2026) to municipal waste-collection windows (Yu et al., 2024). It suggests that time windows are now incorporated into realistic routing models rather than treated as an optional extension.

Sustainability has also emerged as a major research direction. Green and carbon-aware routing is increasingly integrated into MDVRP formulations, while research on electric vehicle routing has steadily expanded throughout the review period. (Pu et al., 2022),(S. Wang et al., 2022),(Hou et al., 2021). Rather than being investigated as a standalone problem, electric vehicle routing is commonly combined with other operational features, particularly time-window constraints, collaborative logistics, and time-dependent travel, indicating a shift toward more comprehensive and application-oriented optimization models. (Y. Wang et al., 2026),(Rabbanian et al., 2023),(Y. Wang et al., 2023).

Established routing variants, including pickup-and-delivery, split-delivery, heterogeneous-fleet, and collaborative MDVRPs, continue to receive sustained research attention. (Dubey & Tanksale, 2024), (J. Zhang et al., 2023), (Soriano et al., 2022), (Y. Wang, Li, Guan, Fan, et al., 2021). At the same time, growing interest in dynamic and stochastic formulations reflects a growing recognition of uncertainty and the need for real-time decision-making in practical logistics operations. (Wu et al., 2026), (Jiang et al., 2025), (Y. Wang et al., 2022). In contrast, drone-assisted delivery and cold-chain logistics remain underexplored in recent MDVRP literature. Although these application areas have considerable practical significance, their relatively limited representation suggests that they remain emerging research directions with substantial opportunities for further methodological development. Figure 3 shows the prevalence of the problem-variant classes across the reviewed studies.

5. Solution Methodologies

Metaheuristics remain the dominant solution paradigm in contemporary MDVRP research, reflecting their ability to balance solution quality, computational efficiency, and modeling flexibility. Their continued prevalence indicates that exact optimization alone remains insufficient to solve large-scale, feature-rich MDVRP variants, in which multiple operational constraints substantially increase computational complexity. Consequently, algorithms such as variable neighborhood search (Bezerra et al., 2022), (Alinaghian, Jamshidian, Tirkolaee, et al., 2021), (Sadati et al., 2021), ant colony optimization, genetic algorithms (Stodola & Nohel, 2023; Xue, 2023), simulated annealing, and other bio-inspired approaches continue to form the methodological foundation of the field (Y. Zhang et al., 2026), (Lim et al., 2025), (Yesodha & Amudha, 2022).

Exact optimization methods remain an important component of MDVRP research, but their role has become increasingly specialized. These methods are primarily applied to small or structurally tractable instances and are often incorporated within matheuristic frameworks to optimize decomposed subproblems (Huang et al., 2024), (Bani et al., 2023), (Arias Londoño et al., 2023). However, these methods are rarely used as standalone solvers and are more commonly integrated with clustering procedures, local search, or metaheuristics. This integration indicates that current research considers machine learning a complementary component that enhances, rather than replaces, conventional optimization techniques. Learning-based approaches represent the most rapidly developing methodological direction. Their primary advantages are fast inference at deployment and the ability to generalize across instance sizes once trained. These approaches include transformer policies, graph-attention reinforcement learning (Lu et al., 2026), (K. Zhang et al., 2023), and deep reinforcement learning for dynamic delivery (H. Liu et al., 2026; Movahedkor et al., 2026). A notable trend in the literature is the increasing adoption of hybrid solution frameworks. By combining multiple optimization paradigms, these approaches leverage the complementary strengths of different methods. For example, clustering- or learning-based models are used for customer assignment, metaheuristics for route improvement, and exact optimization for restricted subproblems. While hybridization has improved solution quality and computational performance, it also introduces greater algorithmic complexity and additional parameter tuning requirements. Furthermore, relatively few studies report systematic ablation analyses, making it difficult to quantify the contribution of each component and limiting the reproducibility of proposed frameworks. Metaheuristics continue to serve as the primary optimization engine for large-scale MDVRPs, exact methods contribute computational rigor to tractable subproblems, and learning-based techniques increasingly support high-level decision-making within hybrid optimization frameworks. Figure 4 illustrates the evolution of solution paradigms across the review window.

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6. Benchmarking Practice

Recent research on the Multi-Depot Vehicle Routing Problem (MDVRP) demonstrates significant heterogeneity in benchmarking practices. While classical benchmark sets remain a common foundation for algorithm comparison, an increasing number of studies employ modified, synthetic, or proprietary real-world datasets to evaluate feature-rich problem variants (Y. Wang et al., 2026)(Arias Londoño et al., 2023)52]. This diversification reflects the growing complexity of contemporary MDVRP formulations but has reduced the comparability of reported results across studies. Among classical benchmarks, Cordeau's MDVRP and MDVRPTW instances are the most widely adopted reference sets(Yu et al., 2023) (Stodola & Nohel, 2023)(Bezerra et al., 2022)(Sadati et al., 2021), followed by Solomon-derived instances (Yu et al., 2024)(Xue, 2023)(Huang et al., 2021). Their widespread use enables direct comparison of algorithmic performance and has contributed to consistent benchmarking over many years. However, these benchmark sets were originally designed for traditional routing problems and do not effectively capture new elements such as electric vehicles, collaborative logistics, dynamic operations, or drone-

assisted delivery. Consequently, many recent studies either enhance existing benchmarks or develop new datasets to incorporate these additional constraints. (Y. Wang et al., 2026)(Arias Londoño et al., 2023) .

The increasing use of real-world datasets highlights a growing emphasis on practical applicability. Studies focusing on applications such as fuel distribution (Bani et al., 2023), retail logistics(Mogale et al., 2025), and cold-chain transportation (Nozari & Yordanova, 2026) provide valuable evidence of algorithm performance under realistic operating conditions. However, these datasets are rarely made publicly available, which limits reproducibility and prevents subsequent studies from conducting direct comparative evaluations.

Synthetic and modified benchmark instances partially address these limitations by enabling controlled experimentation and supporting the evaluation of emerging MDVRP variants. Synthetic datasets are particularly valuable for large-scale computational experiments and data-intensive learning approaches. (Tavana et al., 2026)(Lu et al., 2026)(Zou et al., 2022), whereas modified benchmark sets preserve some continuity with established benchmarks while incorporating additional operational characteristics (Y. Wang et al., 2026)(L. Fan, 2024)(Arias Londoño et al., 2023). Nevertheless, the lack of standardized modifications across studies limits cross-study comparability and complicates objective performance assessment.

However, the absence of standardized modifications across studies restricts cross-study comparability and complicates objective performance assessment. Overall, the literature reveals a trade-off between realism and benchmarking consistency. Classical benchmark sets support reproducible comparisons of algorithms but have limited applicability to modern MDVRP variants. In contrast, real-world and customized datasets better represent practical logistics systems but reduce reproducibility and comparability. The development of standardized, publicly available benchmark datasets for feature-rich MDVRP variants would enhance methodological consistency and enable more reliable comparative evaluation. Figure 5 summarizes the benchmark categories used in the reviewed studies.

7. Constraints

Vehicle capacity and time windows constitute the primary constraints in contemporary multi-depot vehicle routing problem (MDVRP) formulations. Vehicle capacity is addressed in nearly all reviewed studies (Sadati et al., 2021), and time windows have become a standard operational requirement across diverse applications (Yu et al., 2024; Dursun & Özger, 2022). In addition to these core constraints, recent research increasingly incorporates application-specific operational features. Electric vehicle routing introduces a distinctive set of constraints, with battery capacity and charging requirements typically modeled alongside time windows. This approach reflects the integration of energy management and service scheduling in electric logistics systems (Arias Londoño et al., 2023; Y. Wang et al., 2023). Other application-specific constraints, such as route duration, depot capacity, multiple trips, and split delivery, are commonly associated with waste collection, replenishment, and pickup-and-delivery operations

(Dubey & Tanksale, 2024)(Y. Wang, Li, Guan, Fan, et al., 2021)(Bani et al., 2023)(Huang et al., 2021) (Huang et al., 2024)(Cavecchia et al., 2025)(Vieira et al., 2023).

Emerging applications introduce further specialized constraints. For example, drone-assisted routing combines synchronization, energy, and temporal constraints (Nozari & Yordanova, 2026)(C.-M. Chen et al., 2023). In contrast, explicit carbon-emission constraints remain relatively uncommon, despite increasing interest in sustainable logistics (Şahin & Yaman, 2024). This suggests that emissions are more frequently treated as optimization objectives than as hard operational constraints.

Overall, recent MDVRP formulations are distinguished by the integration of multiple interacting constraints, rather than the addition of isolated constraints. The growing co-occurrence of temporal, energy, capacity, and synchronization constraints significantly increases problem complexity and has led to greater adoption of hybrid and decomposition-based solution methods. Figure 6 presents the constraint co-occurrence patterns identified in the reviewed studies.

8. Objectives

Travel cost remains the primary objective in multi-depot vehicle routing problem (MDVRP) research, with distance most commonly used as its surrogate measure (Becker et al., 2026)(Wan et al., 2023)(Sadati et al., 2021) (Stodola & Nohel, 2023)(Bezerra et al., 2022). Recent studies increasingly incorporate additional objectives such as service quality, sustainability, and operational performance, reflecting the growing complexity of practical logistics systems. Service oriented objectives such as travel time, makespan, and customer satisfaction have received greater attention alongside traditional cost minimization (Shang et al., 2023)(Cavecchia et al., 2025)(Yu et al., 2024)(Y. Wang et al., 2022). Environmental sustainability has also become a significant research focus, with carbon-emission objectives now appearing more frequently than energy-consumption objectives (Pu et al., 2022)(S. Wang et al., 2022)(Hou et al., 2021) (Y. Wang et al., 2026)(Xu et al., 2023). This trend suggests that recent studies increasingly evaluate environmental impact in terms of emissions rather than energy use, aligning optimization objectives with sustainability and policy considerations. In contrast, objectives related to fleet utilization, fairness, profit, and operational risk remain relatively uncommon.(Bezerra et al., 2022)(Soriano et al., 2022)(Y. Wang, Li, Guan, Xu, et al., 2021) (Hu et al., 2023), indicating that these aspects remain underexplored despite their practical relevance.

The diversification of objective functions has accelerated the adoption of multi-objective optimization while simultaneously reducing the comparability of reported results. Differences in emission and energy models, objective formulations, and performance metrics make direct comparisons across studies increasingly difficult. Developing standardized objective definitions and evaluation metrics would therefore improve the reproducibility and comparability of future MDVRP research.(Zou et al., 2022)(Q. Zhang et al., 2022)(Zabihian-Bisheh et al., 2022)(Pu et al., 2022)(S. Wang et al., 2022)(Hou et al., 2021). This is a subtle but important reproducibility problem that the field has not yet addressed. Figure 7 summarizes the distribution of optimization objectives across the reviewed studies.

9. Trends and Closing Observations

The reviewed literature indicates continued growth in MDVRP research between 2021 and 2026, accompanied by increasing diversity of applications. Recent studies extend beyond generic distribution problems to application domains such as last-mile logistics.(Choi et al., 2026)(Tavana et al., 2026), waste collection and recycling (Kantekin et al., 2026) (Yu et al., 2024), petroleum replenishment (Bani et al., 2023), disaster relief (Xu et al., 2023), cold-chain logistics (Nozari & Yordanova, 2026), and public transit scheduling (Shang et al., 2023)(C. Wang et al., 2021). Retail and multi-depot freight distribution also feature regularly(Mogale et al., 2025)(Cavecchia et al., 2025). This expansion reflects the increasing adoption of MDVRP models in application-specific logistics environments.

Methodologically, the field has remained relatively stable. Metaheuristics continue to dominate solution approaches, while learning-based methods have gained increasing attention, particularly in recent years, and are most often integrated within hybrid optimization frameworks rather than used as standalone solvers. At the same time, benchmarking practices have shifted from classical benchmark instances toward modified and application-specific datasets. Two observations emerge from this synthesis. First, benchmarking practices remain fragmented, limiting direct comparisons across studies, particularly for feature-rich MDVRP variants. Second, the growing integration of learning-based and optimization-based methods suggests that future methodological developments are likely to emphasize hybrid frameworks rather than replacing established optimization techniques. Collectively, these findings highlight the need for standardized benchmark datasets and improved reporting practices to support reproducibility and comparative evaluation.

10. Conclusion

This review synthesized 100 studies on the Multi-Depot Vehicle Routing Problem (MDVRP) published between 2021 and 2026. The analysis shows that recent research has progressively shifted from classical capacity-constrained formulations toward feature-rich variants incorporating time windows, electrification, sustainability objectives, heterogeneous fleets, collaboration, and dynamic operating conditions.

Metaheuristics remain the predominant solution paradigm, although recent studies increasingly combine them with exact optimization and learning-based techniques within hybrid frameworks. Benchmarking practices have also evolved, with growing reliance on modified and real-world datasets to evaluate emerging MDVRP variants.

Overall, the reviewed literature indicates that increasing problem complexity has been accompanied by corresponding advances in modeling and solution methodologies. However, the limited availability of standardized benchmark datasets and the lack of consistent reporting practices continue to hinder reproducibility and cross-study comparison. Addressing these methodological challenges would strengthen future comparative research and support the continued development of MDVRP solution approaches.

Declarations

Declaration of competing interests

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Author Contribution

R.F.K.L.: Rafiatun Ferdous Khan Lubaba , M.A.R.H.: Md. Ashiqur Rahman Hridoy , M.A.A.: MD. Aidid Alam R.F.K.L. contributed to the conceptualization, formal analysis, visualization, and writing of the manuscript. M.A.R.H. performed formal analysis, editing, and proofreading. M.A.A. contributed to the writing, editing, and prepared the figures. All authors reviewed and approved the final manuscript.

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Figures

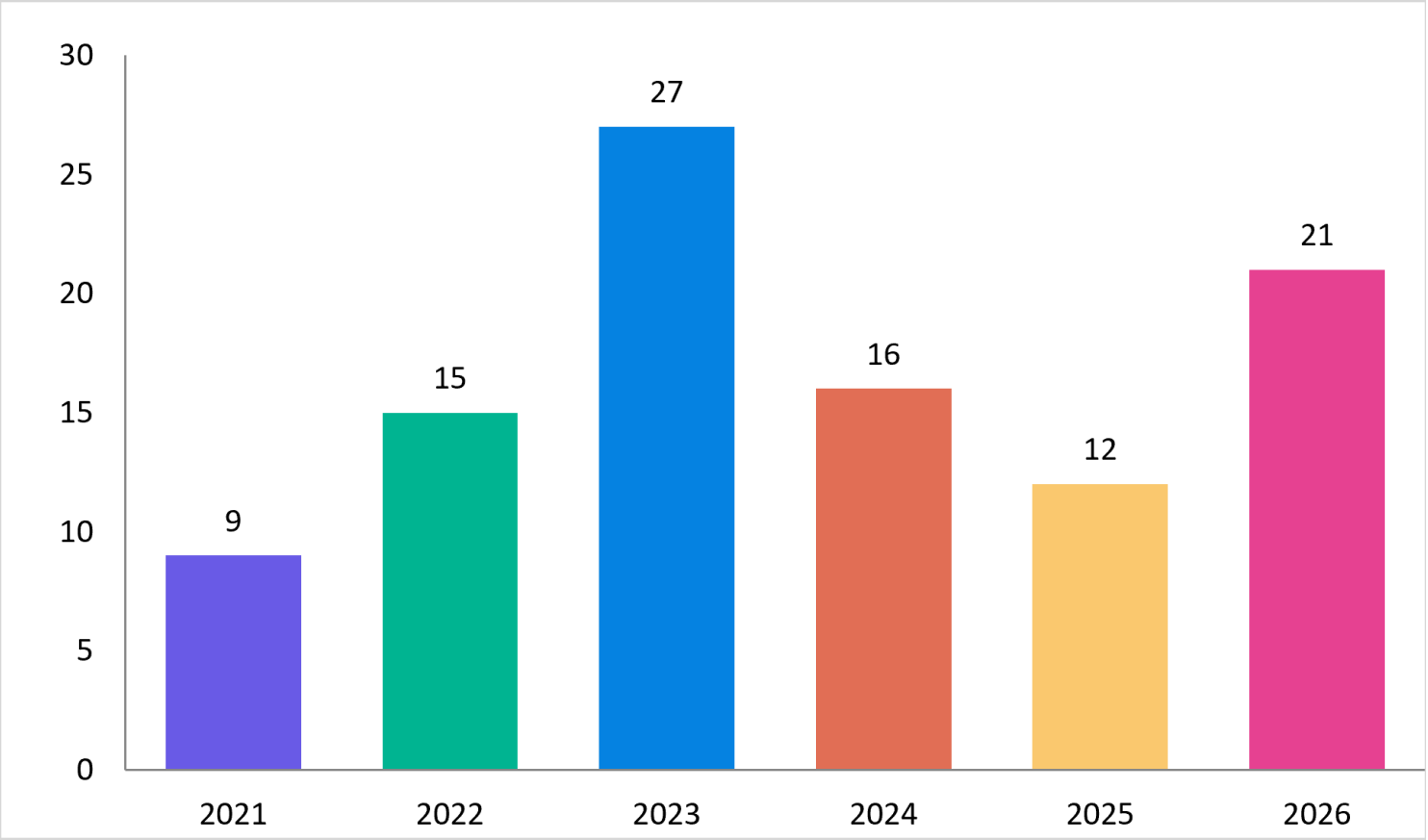


Figure 1

Number of MDVRP studies published per year, 2021–2026.

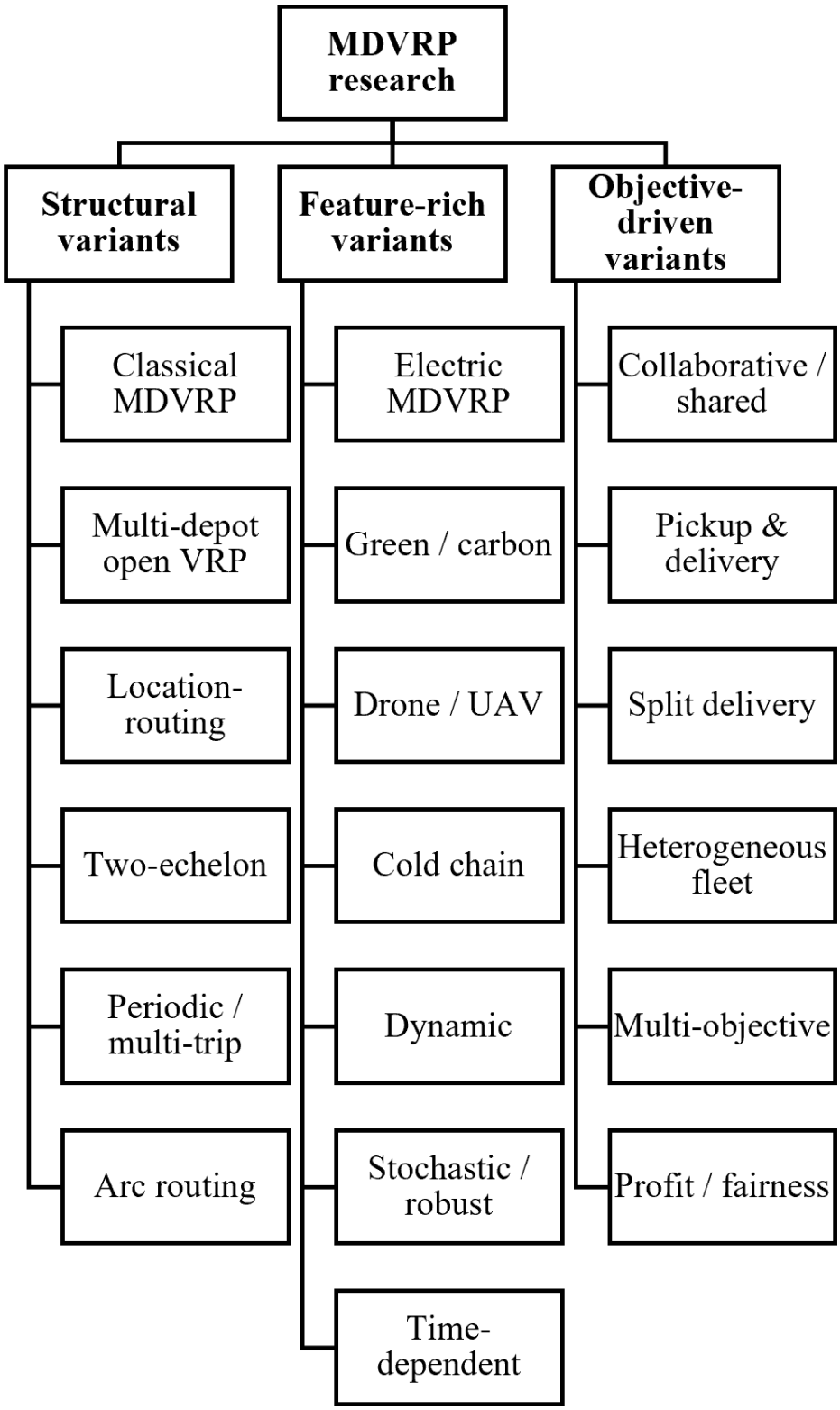


Figure 2

Research Taxonomy of MDVRP variants

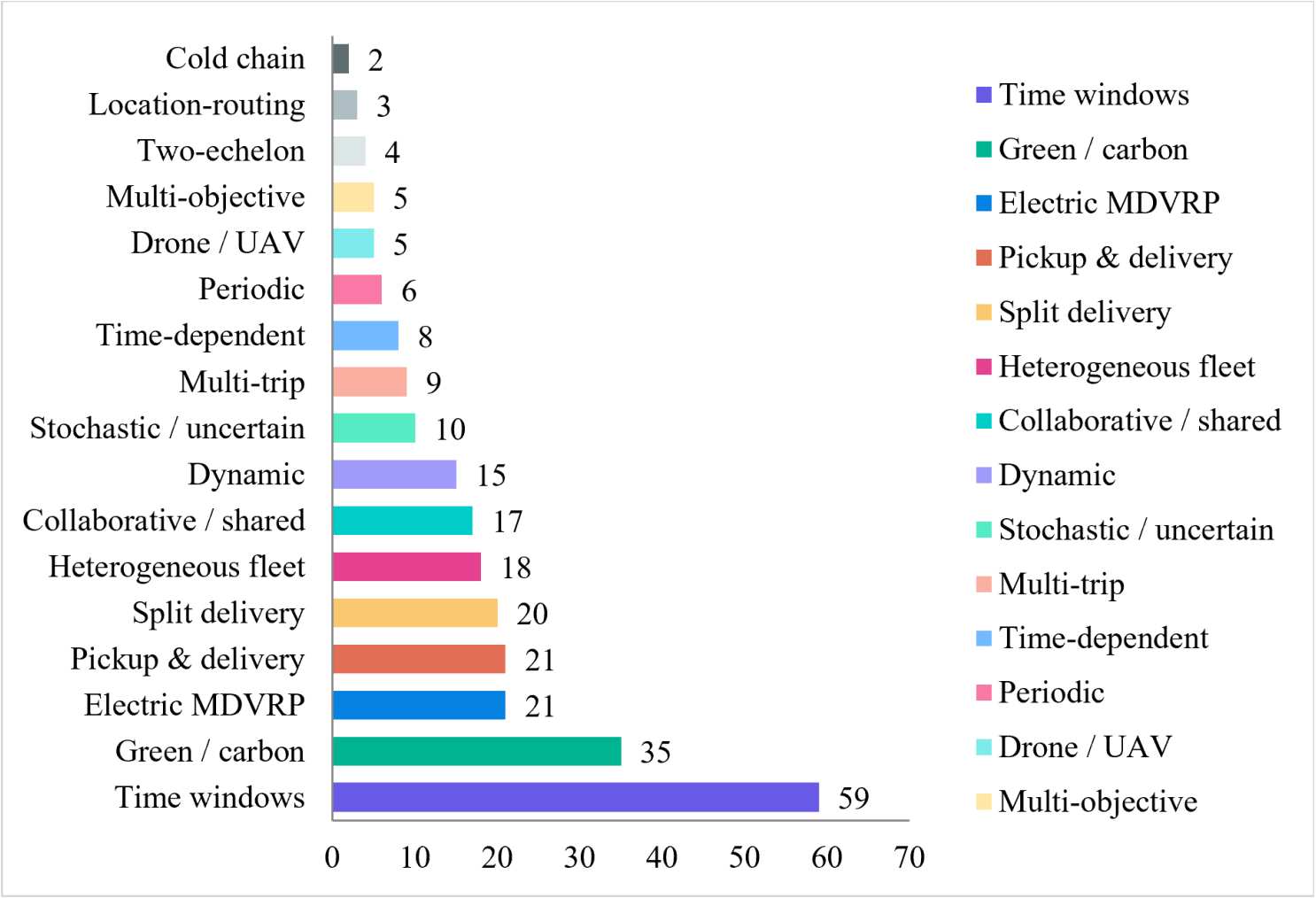


Figure 3

Prevalence of problem-variant classes across the reviewed studies

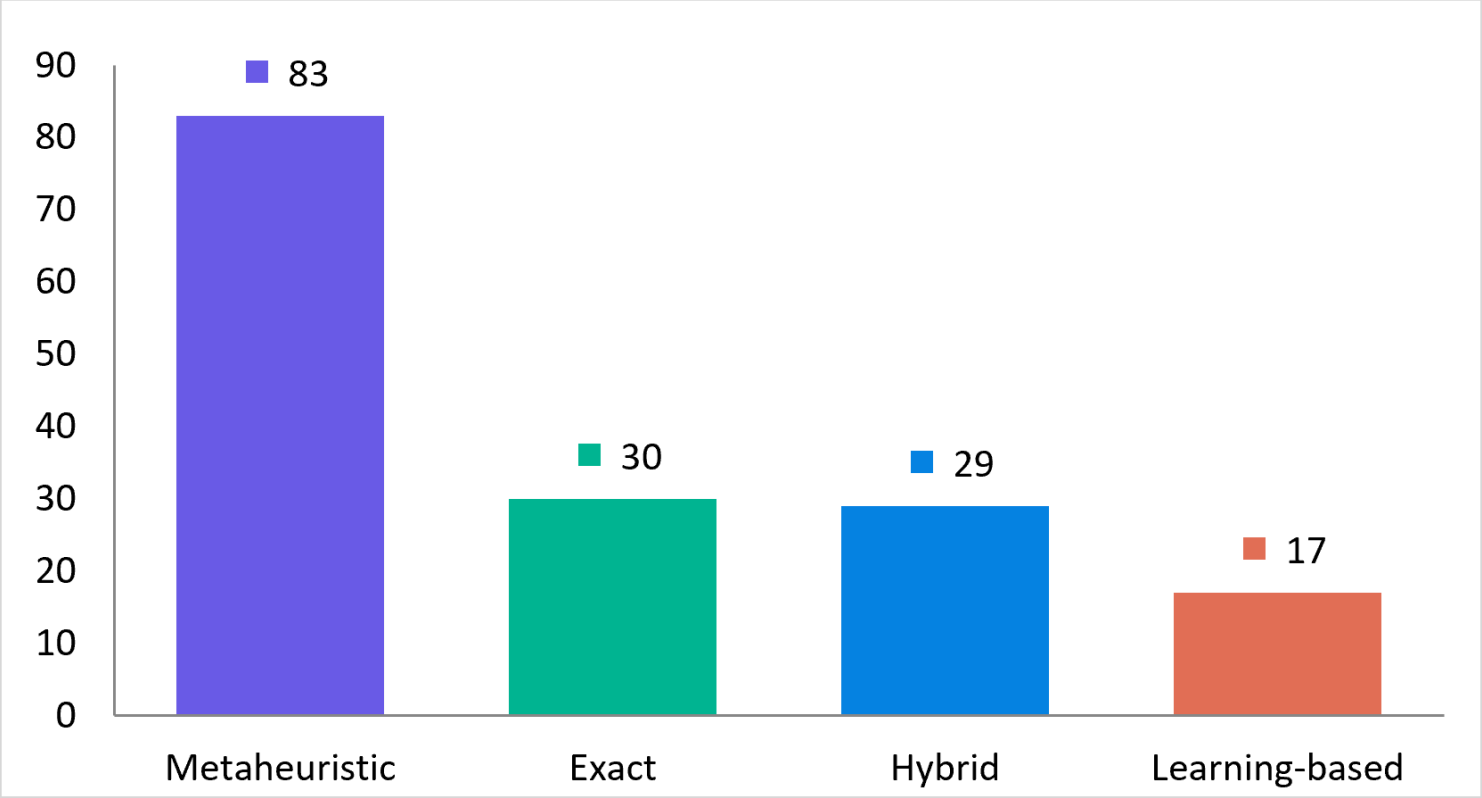


Figure 4

Distribution of solution paradigms across the reviewed studies

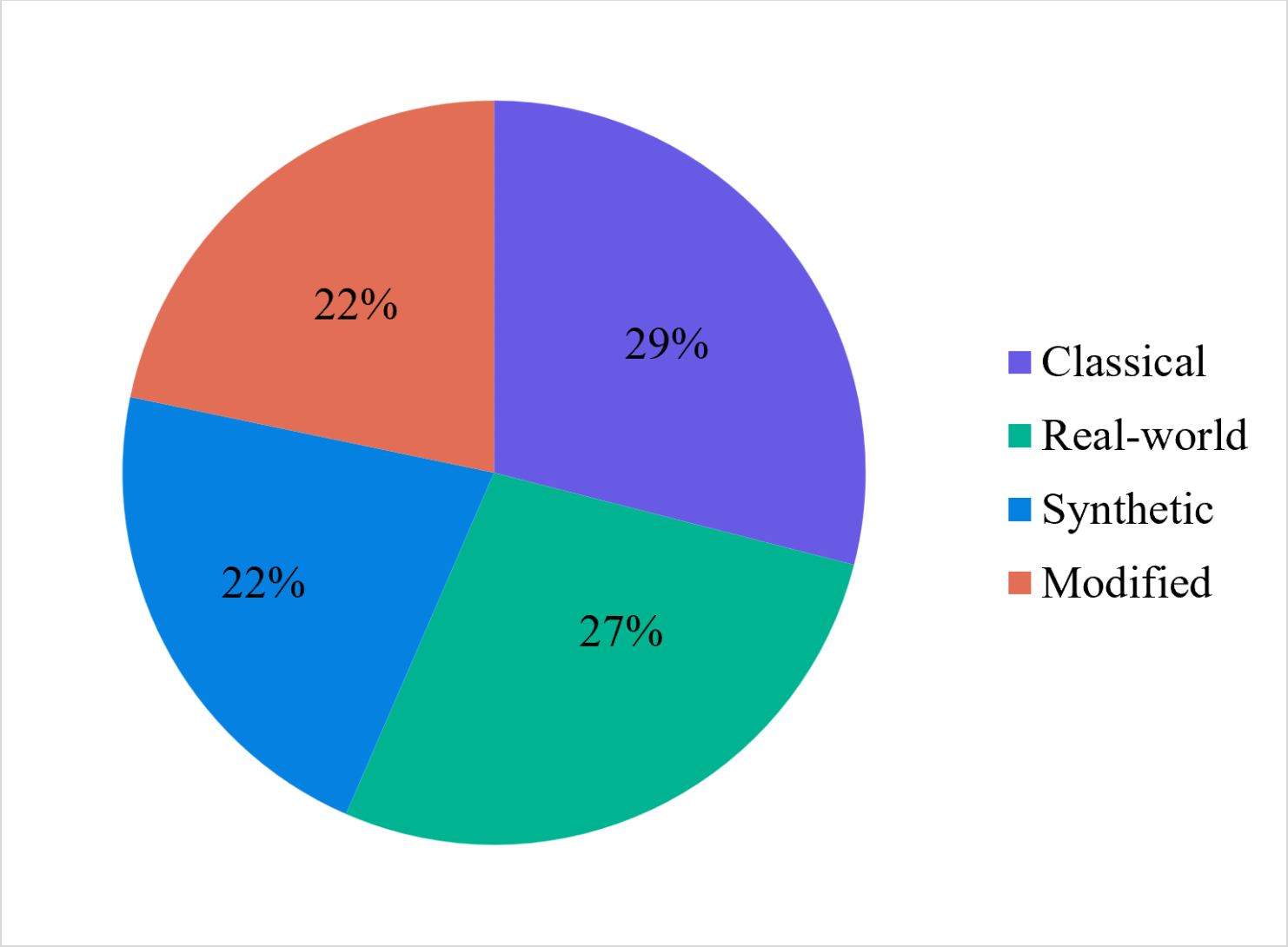


Figure 5

Usage of benchmark-instance categories(non-exclusive)

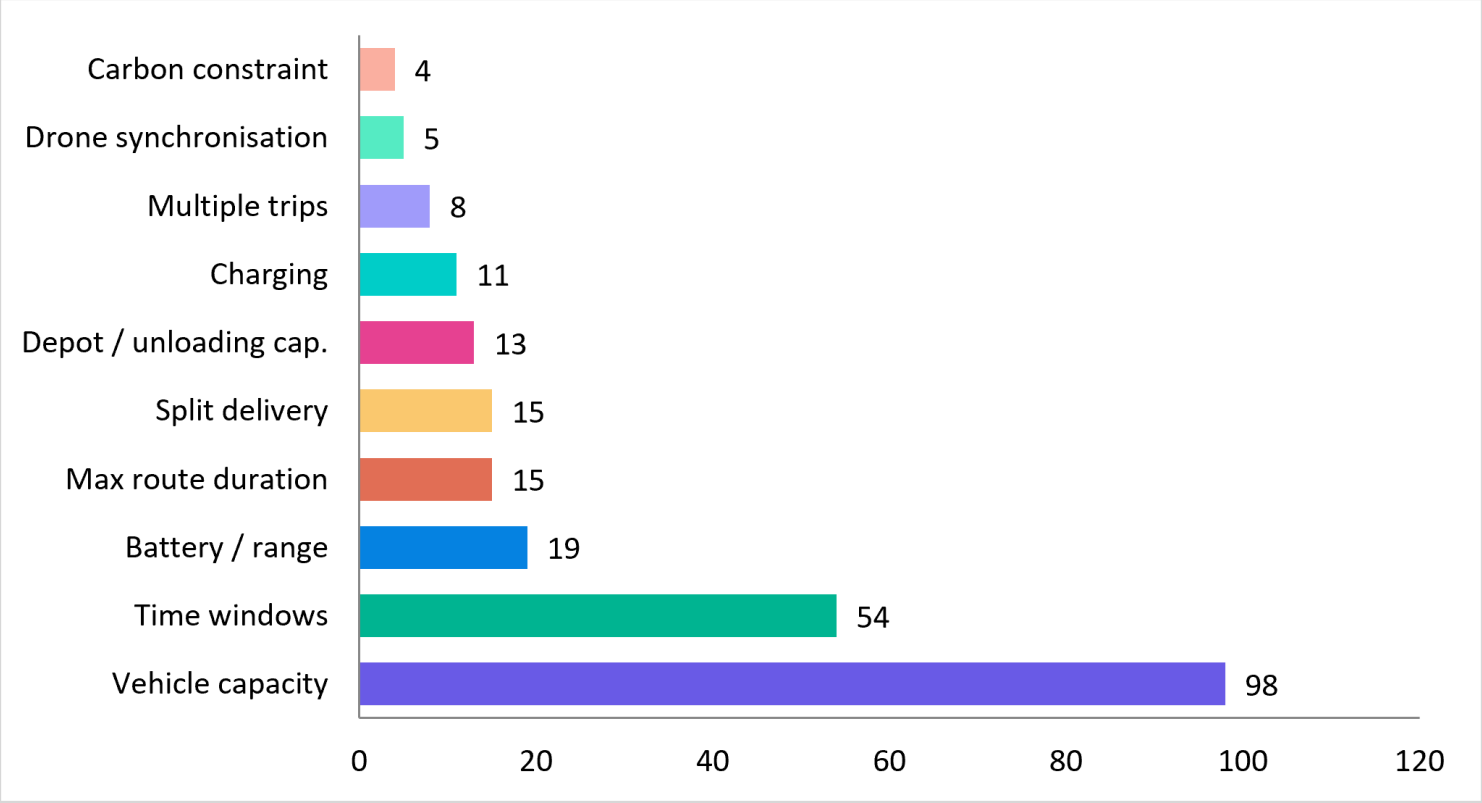
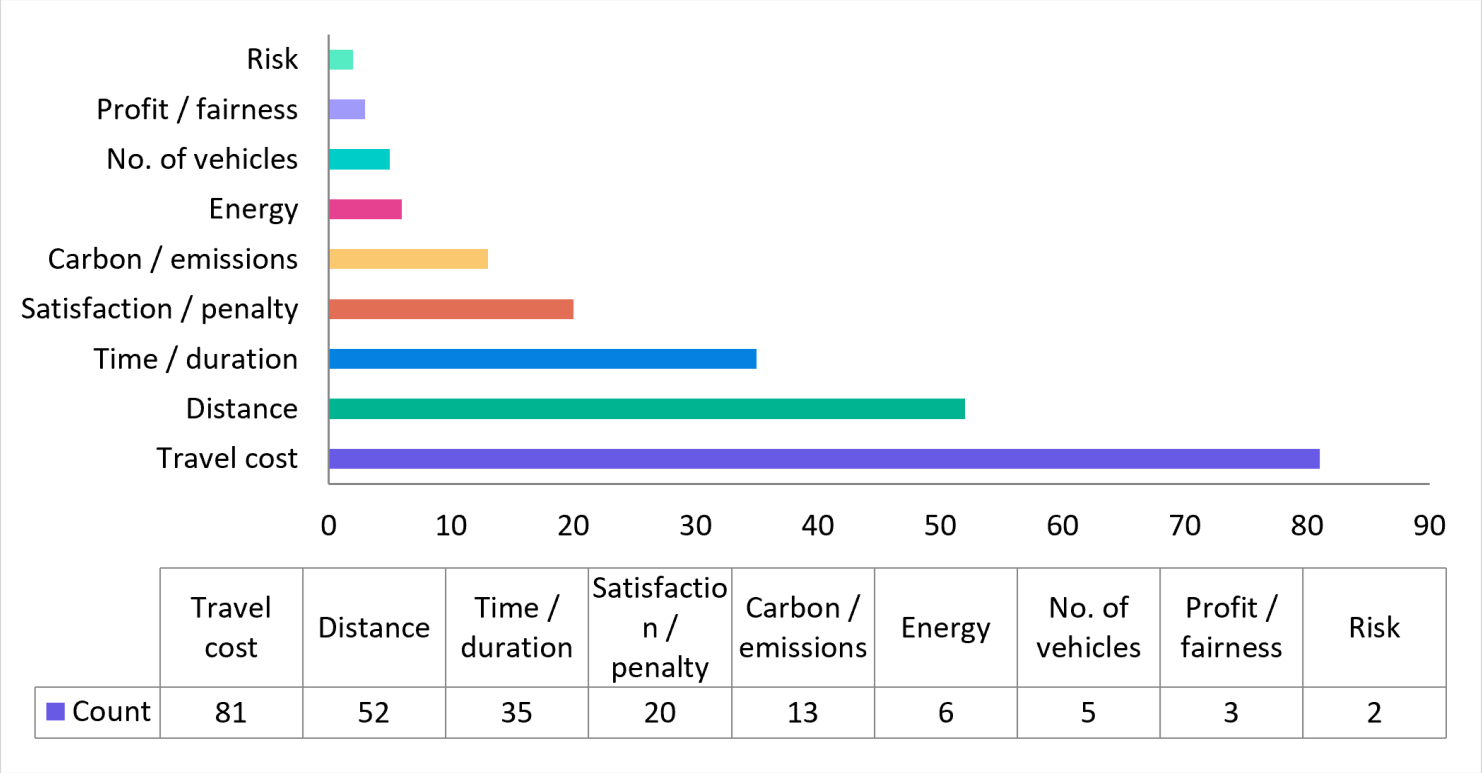


Figure 6

Usage of benchmark-instance categories(non-exclusive)



	Travel cost	Distance	Time / duration	Satisfaction / penalty	Carbon / emissions	Energy	No. of vehicles	Profit / fairness	Risk
Count	81	52	35	20	13	6	5	3	2

Figure 7

Frequency of key constraints across the reviewed studies

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixA.docx