Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2026 (44) 12** : 1–27.
ISSN-0037-8712
doi:10.5269/bspm.83040

Multi-Depot Vehicle Routing Problem: A Comprehensive Review

Ranjeeta, Mohit Kumar Kakkar and Priyanka

ABSTRACT: Transportation plays a significant role in today's era. To ensure on-time delivery in logistics, it is crucial to effectively manage the delivery fleet. This review paper presents a comprehensive analysis of 79 research studies related to single-depot and multi-depot vehicle routing problems. Among these, 40 papers focus on models without time windows, while 35 papers address problems that include time window constraints and one is review paper based both time and without window constraint. In terms of problem structure, 59 papers are based on multi-depot vehicle routing problems, 17 papers consider single-depot vehicle routing problem with one review paper related to the single vehicle routing problem and 3 papers based on complexity classes and comparison of some classification algorithms. Moreover, the study contains different solution approaches that solve NP-hard problems. The main purpose of this review is to identify trends, methodologies, and key developments in the field of vehicle routing problems. Additionally, comparative differences between models with and without time windows and between single and multi-depot vehicle routing problems is also explored.

Keywords: Multi-depot vehicle routing problems, NP-hard problems, methodologies, solution approaches.

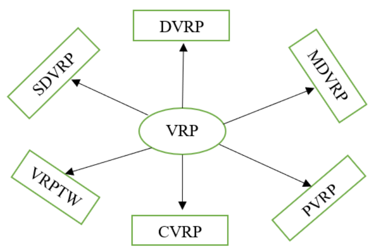
Contents

1. Introduction

Transportation problems play a crucial role in the efficiency and profitability of modern industrial and commercial systems. Every business and company depends on a well-organized transportation system to move raw materials, goods or finished products from suppliers to purchasers with minimal cost and highest efficiency. The purpose of these operations is optimizing factors such as total travelled distance, travel time, fuel consumption, and delivery cost, which together form the basis of transportation optimization problems. Such challenges are highly based on supply chain management, where effective routing and scheduling directly impact on service quality and operational performance. Among these, one of the most researched areas and widely applied optimization problems is the Vehicle Routing Problem (VRP). The

2020 *Mathematics Subject Classification:* 90B06, 90C27.
Submitted March 27, 2026. Published June 08, 2026.

concept of VRP was first introduced by Dantzig and Ramser in 1959, who proposed a mathematical model to determine the most cost-efficient routes for gasoline delivery from a central depot to multiple service routing, logistics, and distribution network optimization [1]. Many types of VRP includes Periodic VRP, Stochastic VRP, Distance or Time VRP, Capacitated VRP. In Period VRP types vehicles plan deliveries not on a single day. Vehicles plan services on several and specific days. Stochastic VRP the type of VRP customers demand randomly changes, also travel time, service time and customers availability is uncertain. Distance or Time VRP in this problem focuses on finding vehicle best route so that minimize travel distance and travel time. Capacitated VRP have limited capacity vehicles and fulfil all customers' demands without exceeding its limits. VRPTW (vehicle routing problem with time window) is a type of problem where vehicle serve all customer with given time period. MDVRP is a type of VRP which is preferred by companies & warehouses having more than 1 depot and each depot has own group of vehicles. Figure 1 shows different types of VRP.



VRP: Vehicle Routing Problem, MDVRP: Multi Depot Vehicle Routing Problem, VRPTW: Vehicle Routing Problem with Time Windows, CVRP: Capacitated Vehicle Routing Problem, PVRP: Periodic Vehicle Routing Problem, SDVRP: Stochastic Vehicle Routing Problem, DVRP: Distance or Time Vehicle Routing Problem.

Figure 1: Types of VRP

1.1. Multi-Depot Vehicle Routing Problem (MDVRP)

MDVRP is an extension of Vehicle Routing Problem. In MDVRP there are multiple depots and each vehicle start and ends its routes from assigned depot [5]. Each vehicle has own group of vehicles group. MDVRP used for real-world logistics systems and large-scale distribution networks where companies have multiple warehouses like online companies (Amazon, Flipkart and Myntra). Main objective of MDVRP is minimize total transportation cost, travel time, fuel use and quickly deliver customers' orders without waiting time. The MDVRP is a very complex and NP-Hard problems. Various solutions approaches have been proposed to solve this type of problems. Exact Methods, heuristic and metaheuristic approaches solve this type of problems. Small instances problem is solved by exact methods because exact method gives prefect solution but large instances problem is solved by heuristics approaches as it gives quick and fast solution but not always perfect one. Big and complex problems solved by metaheuristics approaches such as Genetic Algorithms, Ant Colony Optimization and Particle Swarm Optimization. Recently, hybrid approaches combining metaheuristics with machine learning techniques have been promising in tackling large-scale MDVRPs. Thus, MDVRP is one of the most realistic and significant routing problems. The literature shows a steady evolution based on early mathematical models to advanced metaheuristics and at present AI-driven optimization techniques. This trend underscores highlights the importance of MDVRP in achieving cost reduction, resource optimization, and eco-friendly logistics solutions. Overall, the aim of MDVRP is to provide a more realistic, flexible, and cost- efficient logistics model that can better reflect modern distribution networks compared to single depot VRPs. In general, the objective of the multi-depot vehicle routing problem (MDVRP) is meant to develop optimal delivery or transportation routes when more than one depot is available. Figure 2 represents the working of a MDVRP.
As opposed to the classical single depot VRP, MDVRP customers to most suitable depots and optimizing vehicle routes in such a way that:

- Mixed fleets, traffic limits or sustainable logistics requirements.

- Total transportation costs are reduced - with distance included, time, and fuel consumption.
- Vehicle capacity and time window constraints are satisfied, ensuring realistic and viable deliveries.
- Depot workload distribution is balanced, so that no single depot is overloaded or underloaded.
- Service quality is improved by minimizing delay and fulfilling customer demands efficiently.

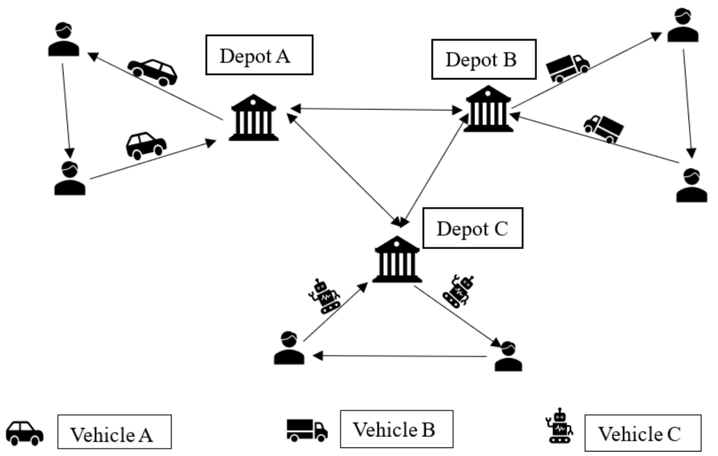


Figure 2: An illustration of MDVRP

1.1.1. ***Multi-Depot Electric Vehicle Routing Problem (MDEVRP)****.*
The MDEVRP is a type of MDVRP. In MDEVRP delivery vehicles are powered by electricity rather than fuel/diesel. In these problems multiple depots have a set of electric vehicles [12]. Each electric vehicles starts forms its assigned depot, visits all customers and return either to same or another depot. Unlike conventional vehicles, electric vehicles have limited driving capacity and require recharging at charging stations. Therefore, MDEVRP design routes considering customers demand, travel time, battery consumption and locations of charging stations. Main objective of MDEVRP is to minimize total travel distance, energy consumption, charging cost and carbon emissions. Figure 3 represents the working of a Multi-Depot Electric Vehicle Routing Problem covering all the routes from depots to different customers.

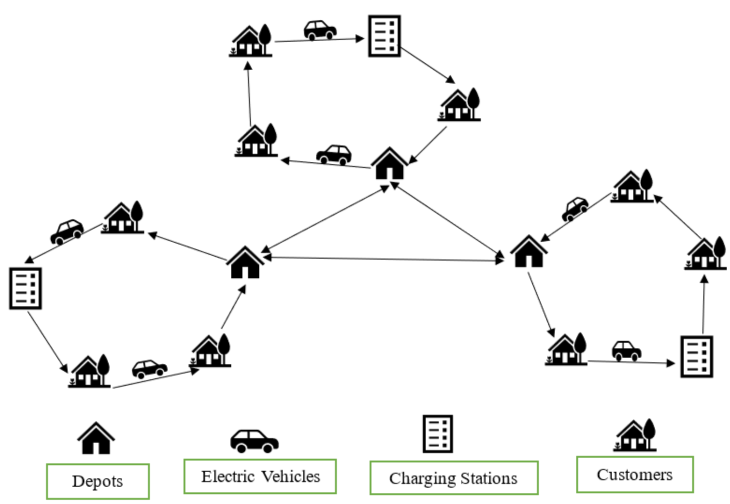


Figure 3: Multi-Depot Electric Vehicle Routing Problem

1.1.2. *Multi-Depot Green Vehicle Routing Problem (MDGVRP).*

The MDGVRP is also a type of Multi-Depot Vehicle Routing Problem [17]. In this problem, green vehicles fleets may be electric, hybrid and powered by alternative clean fuels. These vehicles have limited capacity and also require recharging or refuelling during their routes. Main objective of multi-depot green vehicle routing problem is to satisfy the demands of all customers and also minimize total cost, travel distance, fuel and CO_2 emissions. Figure 4 reveals the working of a multi-depot green vehicle routing problem covering the all routes from depots to different customers. The primary differences between the MDEVRP and MDGVRP are shown in Table 1. MDEVRP focuses on routing problems related to electric vehicles only, where batteries are the only energy source accessible when charging is necessary. On the reverse side, MDGVRP includes into account an array of environmentally vehicles types, includes low-emission, electric, hydrogen and hybrid vehicles using different sources of energy. In contrast with MDEVRP, MDGVRP provides a more realistic and comprehensive frame work for environmental transportation and logistics.

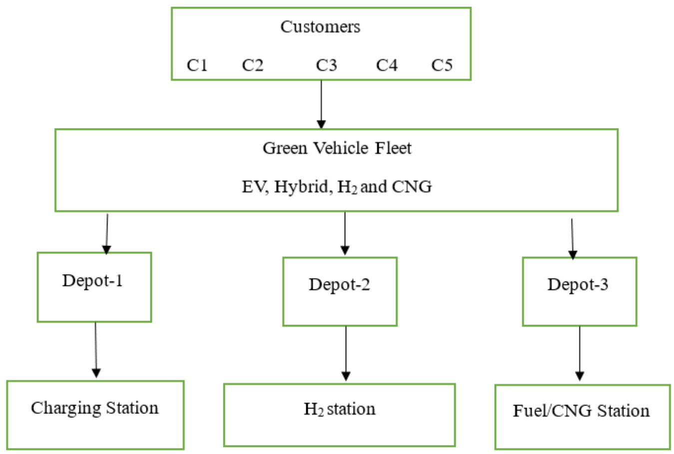


Figure 4: Multi-Depot Green Vehicle Routing Problem

Table 1: Difference between MDEVRP and MDGVRP

Features	MDEVRP	MDGVRP
Types of vehicles	Only electric vehicles	Electric, hydrogen, low-emission vehicles and hybrid
Energy source	Battery only	Battery, fuel and hybrid
Charging	Mandatory	Depend on vehicle type
Environmental focus	Indirect	Direct and strong
Scope	Narrow	More realistic and broader

2. Literature Review

The Vehicle Routing Problem (VRP) was first introduced by Dantzig and Ramser (1959) to design optimal delivery routes for a set of vehicles serving several customers while reducing travel cost [1]. Since that time, many extensions of the classical VRP have been designed to represent real world transportation and logistics issues. From these, the Multiple depot Vehicle Routing Problem (MDVRP) has acquired considerable importance as it allows multiple vehicles to operate simultaneously, each allocated to separates routes, with the aim of importance as it allows multiple vehicles to operate in parallel, each assigned to different routes, with the goal of improving delivery efficiency and optimizing operational costs. Hartmanis et al. (1971) the theory of computational complexity, which evaluated the challenges of performing different tasks, was discussed in this research. Its primary objective was to calculate the time and space required to perfume the calculation. To improve comprehension of the theory, the paper carefully and methodically presented the main principles and along with major data [2]. Bovet et al. (1992) for the purpose to investigated different complexity classes more broadly, this paper proposed a uniform computation model. It provided complexity classes of entire language and provided suitable and necessary demands for separating relativized complexity classes. In an effort to show how these results were applied to specific complexity classes, the study also provided examples [3]. Delimata et al. (2010) this investigation two distinct types of nondeterministic rules and shown how they improved decision table classification quality. Experiments showed that algorithm based on limitation and inhibitory non-deterministic concept often performed normal deterministic rules [4].

Chavez et al. (2016) the multi-depot vehicle routing problem with backhauls (MDVRPB), an NP-hard logistic and supply chain problem, was investigated in this research. It focused on a specific case in which backhaul customers needed to be supplied while product pickup took place [5]. Li et al. (2016) in this paper, an original variant of the multi-depot vehicle routing problem with time window in which vehicle could finish at a different depot than they started at was studied. For the purpose to minimize the total price of travel within different constraint, it recommended a hybrid genetic algorithm with adaptive local search [6]. Oliveira et al. (2016) with the goal to minimize the total route cost of the multi-depot vehicle routing problem, the current study proposed a cooperative coevolutionary method. The results showed that the parallel coevolutionary technique produced outstanding outcomes in a brief period of computation time [7]. Bae et al. (2016) the multi-depot vehicle routing problem with time -windows was extended in this research to optimize electronic delivery and installation companies. The computational results showed that the proposed method problems while minimize. It also introduced a mixed integer programming model in place to heuristic and genetic algorithms [8]. Mirabi et al. (2016) studied the multi-depot vehicle routing problem with time windows, that involves vehicles did not have to return to their same depots, was the topic of this article. In compared to FCM and K-means Clustering methods using GA. The results showed enhanced efficiency [9].

Sundar et al. (2017) studied multi-depot routing problem for heterogeneous unmanned air and vehicle types with multiple sensors and motion constraint was studied in this study. It developed a branch-and–cut method that successfully provided optimal solution for large instances after defining the problem as mixed-integer linear programming [10]. Du et al. (2017) proposed to reduce the total calculated transportation risk, this article investigated the multi-depot vehicle routing problem for the transportation of hazardous products. Results showed the effectiveness of the proposed method, involving four bilevel programming approach [11]. Paz et al. (2018) discussed importance of electric vehicles and the significance of establishing a strong power supply and charging network for their successful installation are addressed in this paper. It addressed optimized using the application of mathematical modelling and metaheuristic approaches [12]. Zhou et al. (2018) taken into consideration depots, customer and satellites pickup options, this investigation proposed a unique two-tier city logistical issue related to final-mile e-commerce distribution. Computational results showed the success of the hybrid multi-population genetic algorithm which was created to minimize the total cost of distribution [13]. Guedes et al. (2018) examined to minimized transportation expenses and schedule deviation, this paper studied the real-time multiple-depot vehicle type rescheduling problem under significant problems. It proposed a heuristic method based on truncated column generation and time-space networks, and its findings showed rapid and successful performance even for everyday and large-scale instances [14]. Rabbani et al. (2018) addressed to decrease total journey costs and time window violations, this addressed a multi-depot vehicle routing problem with time windows involving repair and pickup vehicles. It tested and compared a hybrid genetic algorithm to an elementary genetic algorithm, finding that the hybrid method worked faster [15].

Lalang et al. (2019) formulated to decrease total distributed costs with occasional drivers, this investigation designed a multi-depot vehicle routing problem with time window for this purpose to optimize routing options. It examined real-world limitation such truck capacity, client demand and time constraints [16]. Wang et al. (2019) investigated a multi-depot green vehicle routing problem which involved delivery time penalties, period-dependent speeds, and transportation resource sharing. It showed improved financial and environmental outcomes by providing a hybrid heuristic algorithm and bi-objective model to minimize carbon emission and operating costs [17]. Lalla-Ruiz et al. (2020) introduced the multi-depot cumulative capacitated vehicle routing problem was delivered in this research with the aim of minimizing the overall amount of customer arrival times with the goal to enhance service quality. For this purpose, to address the problem properly, it provided a mathematical formulation and a metaheuristic approach [18]. Olariu et al. (2020) examined to arrange trips to vehicles while reducing total costs, this paper solved the multi-depot vehicle scheduling problem. According to graph-theoretic methods and integer linear programming, it proposed three rapid and reliable methods that worked well in benchmark instances [19]. Reyes-Rubiano et al. (2020) studied utilizing elements related to environmental, social and economic sustainability, this research solved an improved multi-depot vehicle routing problem for urban freight transport. It showed the effective use of sustainability factors in routing decisions by providing metaheuristic approach using biased-randomization and variable neighborhood search [20]. Harbaoui Dridi et al. (2020) studied to improve the total trip distance, this study explored a complex multi-variant routing problem involving many vehicles, different depots, pickup and delivery, and time windows. It proposed an original method based on particle swarm optimization that improved previous method [21]. Sadati et al. (2020) introduced to find out what depots in a routing network have been the most significant, the present study proposed a bilevel optimization model called as r-interdiction selective multi-depot vehicle routing problem. For the purpose to evaluate the impact of delays and improved routing options, it used enumeration and tabu search techniques, describing the problem as an attacker-defender game [22]. Brandao et al. (2020) developed a multi-depot open Vehicle routing problem, where many depots are used and vehicles fail to return to the depot after delivery, was studied in this paper. The results shown that the method executed very well on benchmark problems and proposed a new Iterated Local Search algorithm that used past search history to find better solutions [23]. Mao et al. (2020) investigated a time-windows electric vehicle routing problem by using account of many recharging methods including battery swapping and half recharging. It designed a hybrid ant colony optimization approach and a mixed integer programming model. The results showed improved productivity and cost saving under many recharging methods [24].

Lim et al. (2021) proposed a mixed -integer programming model was given in this research to solve the multi-depot spilt delivery vehicle routing problem with many customers visits and heterogeneous vehicles. It designed a showed how split- delivery improves efficiency and gives competitive outcomes [25]. Cueto et al. (2021) presented to improve depot locations, fleet sizes and daily routing decisions, this investigation presented a solution method for a multi-trip vehicle routing problem with time periods, its proposed exact and heuristic methods winning first prize in an optimization competition and produced economical, accurate and quick solutions with near-optimal results [26]. Osorio-Mora et al. (2021) introduced a new cumulative vehicle routing problem for home health care logistics including many non-fixed depots and emergency trips was addressed in this study. For the purpose to minimizing caregiver delayed latency(overtime), it developed a mixed-integer linear programming model. Computational results showed the impact of geographical distribution and changes in solver performances [27]. F Kocaturk et al. (2021) examined the multi-depot heterogeneous vehicle routing problem with backhauls and a novel mathematical formulation for this related routing problem was developed. It provided a hybrid VNS-based meta heuristic that performed CPLEX and basic VNS to find optimal solution for small instances [28]. Y Wang et al. (2021) developed a sharing resources and time window assignments strategies are combined to produce a bi-objective model for a multi-depot recycling vehicle routing problem. In real studies, outcomes showed improved operational efficiency, cost reduction and better resource with a hybrid 3D K-means and NSGA-II algorithm [29]. Ghobadi et al. (2021) presented a multi-depot electric vehicle routing problem with recharging station, pickup/delivery and fuzzy time windows constraints. It applied VNS, SA, and A hybrid VNS-SA algorithm and the results showed that hybrid approach performed each of the other methods with regards to speed [30]. Uit et al. (2021) presented a branch-and-cut model for solving multi-depot routing problem with asymmetrical prices was presented in this study. Larger instances than previously reported in the research could be resolved due to the recommended valid inequalities, resulting in greatly reduced optimality gaps [31]. Fan et al. (2021) developed to address the multi-depot vehicle routing problem under time-varying road networks, the researcher developed an integer programming model that takes fuel usage, load, vehicle speeds and penalty costs under consideration. The results of a hybrid genetic algorithm with variable neighborhood search showed improved planning performance and sustainable cost saving [32]. Rabbani et al. (2021), in order to minimize total costs and ensure equal product distribution, this study developed a bi-objective multi-depot vehicle routing model with time periods. The application using a multi-objective simulated annealing techniques and a linearized exact method showed successful outcomes for both small and large-scale issue [33]. Niu et al. (2021) proposed a modified multi-objective learnable evolution model to solve multipurpose vehicle routing problem with stochastic demand. The strategy defeated previous evolutionary algorithms and generate better Pareto results by integrating decision tree learning with a unique genetic structure [34]. Rajabi-Bahaabadi et al. (2021) studied the travel time are considered as correlated random variables instead of independent ones in this paper investigation of a vehicle routing problem with soft time periods. The outcomes of a hybrid Max-Min Ant Colony System with Tabu Search showed that considering travel time correlations into account creates more effective and practical routing solutions [35].

Bouyahyiouy et al. (2022) developed a selective full truckload multi-depot VRP with time widows in an empty return context, focusing on profit maximization. It developed Mixed Integer Linear Model and Genetic Algorithm. Computational results showed that the GA provide better solution quality than CPLEX [36]. Hasanpour et al. (2022) examined to minimize purchasing costs, vehicles use multi-trip open routes and depots share resources in the multi-depot traveling purchaser problem under shared resources. Results showed that a decomposition-based method with heuristic changes could decrease costs by up to 29% and lead to fewer dispatched vehicles [37]. Abu-Monshar et al. (2022) proposed to address the VRPTW with vehicle having different locations and depots, this article introduced an agent-based messaging protocol-based heuristic optimization approach. Compared to benchmark techniques, the outcomes showed a decrease in the number of vehicles used and a faster computing time, leading to higher quality solutions [38]. Scott et al. (2022) studied a multiple depot traveling salesman problem with revisit period constraints and presented as a Lagrangian relaxation method that solved MILP. As compared to CPLEX, the proposed dual-based method provided better outcomes that improved computational efficiency and scalability [39]. Sahin et al. (2022) examined a heterogeneous fleet multi-depot multi-trip vehicle routing problem with time windows and shared depot resources, based on city logistics using both small and large vehicles. Computing outcomes showed that a branch-and-price method performed well in dealing with medium-sized instances [40]. Gu et al. (2022) with the goal to improve time efficiency and depot cooperation, this article examined the multi depot vehicle routing problem and using an Artificial Bee Colony method with depot clustering and a coevolution strategy. Based on experimental data, the proposed ABC method worked better than the GA and significantly better than greedy algorithm [41]. Yilmaz et al. (2022) was examined the electric vehicle routing problem with simultaneous pickup and delivery, taking battery and charging situations constraints into account. Suggested was a modified model, which showed superior and effective results on benchmark instances [42].

Kabadurmus et al. (2023) worked presented a green vehicle routing problem with multi-depot, multi-trip, heterogeneous fleet and split deliveries to minimize total carbon emission. A genetic algorithm and a MILP model were developed the results showed reliable and effective outcomes in real distribution conditions [43]. Khodashenas et al. (2023) developed a two-stage integrated multi-depot vehicle routing model with simultaneous pickup and delivery under ambiguity, to optimize package layout and routing options. Under uncertain circumstances, the model effectively balanced cost, carbon emissions and driver working hours using NSGA-II and MOALO with fuzzy-robust box optimization method [44]. Bezerra et al. (2023) explored a variation of multi-depot vehicle routing problem with time windows focused on minimizing the number of used vehicles rather than overall distance. A smart general variable neighborhood search with adaptive local search was suggested, which significantly decreased the fleet sizes [45]. Chen et al. (2023) created a mixed-integer programming model for a multi-depot vehicle routing problem in time-varying and asymmetric networks, aiming to decrease total distribution costs and environmental impact. For the purpose to solve complex time-dependent routing problems, a hybrid Genetic algorithm with simulated annealing approach was created and it worked effectively [46]. S Xue et al. (2023) a two-stage framework utilizing K-means clustering and an adaptive ant colony method is proposed for a crowdsourced multi-depot vehicle routing problem with time windows. The outcomes showed improved large-scale performance over GUROBI and a cost saving of approximately 10% over standard MDVRPTW [47]. Wang et al. (2023) investigated the electric vehicle routing problem with time windows by integrating smart micro grids, temporal-of -use pricing, and vehicle-to-grid (V2G) operations. In compared to standard methods, a hybrid GA- A* algorithm was proposed, showing better optimal solutions, faster convergence, and improved global search ability [48]. Sluijk et al. (2023) formulated the two-echelon vehicle routing problem with stochastic demands to ensure route feasibility with a high probability. Novel labelling algorithms and successful column generation were proposed, showing reduced solution cost and ensured viability in the face of price uncertainty [49]. F Wan et al. (2023) developed a hybrid ant colony optimization method (BPC-HACO) which is enhanced with simulated annealing and local search. As compared to current methods, experimental results showed competitive performance, faster routes and higher solution quality [50]. Zhang et al. (2023) examined a multi-depot pollution routing problem with time windows to minimize carbon emission and charges in e-commerce logistics. Using the application of tabu search and ant colony optimization algorithms, it has been shown that collaboration between logistics providers greatly enhances saving and sustainability [51].

Jolfaei et al. (2024) investigated a multi-depot vehicle routing problem with roaming delivery locations and hard time windows, aiming to reduce the total travel time and waiting time. It suggested hybrid and heuristic ELS-based algorithms that efficiently solve both small and large situation, improved some of the most common benchmark solutions [52]. Li et al. (2024) suggested a deep reinforcement learning model named MD-MTA to solve multi-depot VRP and multi-depot open VRP using a multi-type attention algorithm. The approach showed outstanding efficiency in handling complex multi-depot routing scenarios, exceeding both traditional and existing DRL baselines [53]. Yüksel et al. (2024) suggested a multi-depot vehicle routing model for post-disaster humanitarian logistics, aiming to reduce the total distribution time while performing perishable supplies. It showed the models effectiveness in emergency aid distribution through incorporating truck-drone collaboration and testing it using GAMS/CPLEX [54]. Londono et al. (2024) proposed a hybrid heuristic technique to the multi-objective multi-depot VRP is to equalize load among routes while decreasing the total distance. By the combination of routes fairness and cost efficiency, the research proved effective performance for large instances, improving the quality of the solutions [55]. Diao et al. (2024) proposed a multi-depot routing model that incorporates vans and driverless vehicles in joint distribution operations to improve collaboration and delivery efficiency. A heuristic algorithm and mixed-integer programming model were designed, and the results showed good cost efficiency with limited sensitivity to operational variables [56]. Fan et al. (2024) developed the multi-depot half-open time-dependent electric vehicle routing problem and created a model to reduce total distribution and charging costs under traffic conditions. It developed the two-stage hybrid ant colony optimization that helped sustainable urban transportation by reducing expenses and carbon emission with outstanding performances [57]. Yu et al. (2024) studied the multi-depot two echelon vehicle routing problem with delivery options (MDTEVRP-DO), in which goods are transported from many depots to satellites and subsequently to customers or pickup stations. A fast simulated annealing heuristic of 36 best benchmark solutions with better computing efficiency, beating the most complex algorithms [58]. DP Kumar et al. (2024) proposed a heuristic for the min-max heterogeneous multi-vehicle multi-depot traveling salesman problem, aiming to reduce the maximum tour-time. For the tested instances, the heuristic generated feasible solutions that were, on average, within 4% of the optimal solution [59]. Ru et al. (2024) established a multi modal transport network in vehicles logistics and improved routes using the tabu search approach. In compared to other methods, the results showed improved route efficiency, grater earning, and improved performances [60]. Bi et al. (2024) suggested the proactive infeasibility prevention (PIP) framework, that combines proactive masks with Lagrangian-based constraint awareness, for guide neural methods for complex VRPs. TSPTW and TSPDL experiments demonstrated that PIP improved solution quality and significantly reduced infeasible solutions [61].

Saxena et al. (2025) suggested the IM-VRM model, which integrates graph neural networks, greedy optimization, and traffic-aware Dijkstra routing. Experiments using real-world datasets outperformed current methods with regard to both fuel efficiency, carbon emission and travel time [62]. Rajagukguk et al. (2025) article examined a multi-depot vehicle routing problem with temporary depots to optimize depot locations, delivery routes and vehicles allocations in Indonesia. The model aimed to minimize distribution costs, enhance supply chain sustainability and improve delivery efficiency in the growing e-commerce and transportation sectors [63]. Kraiem et al. (2025) addressed extended the multi-depot arc routing problems by offering flexible end depots and limiting highway arc to night shifts. When comparison to the single-depot approach, the recommended MILP model reduced total travel time by up to 12% [64]. Cavecchia et al. (2025) a mathematical optimization model has been developed for a real-world multi-depot, multi-period and multi-trip VRP with time windows. The proposed approach fulfilled operational and time constraints while reducing total routing costs [65]. Haslinger et al. (2025), this research modelled a multi-depot electric bus scheduling problem to support the transition to zero emission fleets. It examined optimization models that reduced fleet size, energy consumption and charging stops under realistic operational limitations [66]. Liu et al. (2025) studied the multi-depot pickup and delivery location routing problem with time windows to enhance instant delivery efficiency. It suggested a two-stage multi-tasking any system method that shared understanding across many routing tasks to jointly enhance depot location and routing [67]. Tasdemir et al. (2025) was designed and linearized a mathematical model for the multi-depot simultaneous pick-up and delivery VRP with stochastic pick-up demand. Reduced reliability levels and many depots decreased solution times and improved the probability of finding optimal solutions, based on computational and sensitivity analyses [68]. Xu et al. (2025) examined a cooperative waste collection system to enhance sustainability and transportation efficiency. It illustrated how improved cooperation and profit sharing through central planning could decrease costs by up to 23% [69]. Jeong et al. (2025) recommended a decentralized message-passing algorithms (AMP-R) to successfully address the heterogeneous multi-depot VRP efficiently. The method produced near-optimal solutions with good computational efficiency for many cases, based on the results [70]. Akbay et al. (2025) presented a new dataset for the two-echelon electric vehicle routing problem with limitations such as time windows constraints, partial deliveries and simultaneous pickup and delivery. To help the testing and assessing of complex two-echelon routing algorithms, the dataSet includes small to large benchmark instances with a range of geographical settings [71]. Guezouli et al. (2025) examined the multi-depot vehicle routing problem with time windows by optimizing fleet size, delivery delays and routes. It suggested a green model using clustering and a genetic algorithm to minimize cost and environmental impact [72]. Zhang et al. (2025) implied an improved method for the 3L-SDVRP to reduce the number of vehicles and total travel distance under split delivery and 3D loading constraint. The method provided enhanced outcomes at a lower calculating via enhanced packing, providing new search operators and applying adaptive splitting [73]. Yernar et al. (2025) this review paper examined recent studies on vehicle routing under time uncertainty, focusing on optimal methods, uncertain algorithms and simulated methodologies. It proved how decision-making and efficiency in logistics may be improved in uncertain situations by combining robust optimization, simulation and AI-based adaptive methods [74]. Tanash et al. (2025) addressed a challenging VRP with an array of fleet, customer priorities, soft time frames, and pick-up delivery activities. It provided two effective heuristic (GRASP-VNS and PBACO-VNS) that exceeded benchmark results by producing high-quality solutions with low minimal CPU time [75]. Akkerman et al. (2025) applied regression models were employed in this study to accurately predict total distance in TSP and VRP using geographical and limited data. In compared to heuristic methods, the framework preserved service levels while decreasing travel distance by up to 17% [76]. Fernandez et al. (2025) examined the Commutative VRPTW to minimize cumulative cost while considering hard and soft time windows and environmental impact CO emission. It proposed a GRASP-based metaheuristic and reduced emissions and fuel consumption, especially during soft times and provided better or optimal choices [77]. Jeong et al. (2025) introduced the VRP with underground transportation (VRP-UT) to optimize city deliveries via underground logistics. A hybrid Q-learning and pruning method effectively reduced delivery times, operating costs, and surface traffic jams [78]. Acar et al. (2025) tackled home delivery distributed utilizing a multi-depot general colored with time windows (MD-GCTSP-TW). In scenarios for tests, a mixed -integer model and metaheuristic method exhibited promising and effective results [79].

In this review paper, a total of 79 research papers has been studied. Among these, 75 publication that were published between 2016-2025, including both multi-depot and single-depot routing problems. In addition, three studies compare classification algorithms using non-deterministic and deterministic decision rules and evaluate complexity classes, while one paper represents the foundational study of the vehicle routing problem. The study highlights key developments, methodologies, and optimization techniques that enhance efficiency in multi-depot logistics and transportation systems. The publication data related to MDVRP from 2016 to 2025(Source: ScienceDirect database). The yearly publication count of research articles was extracted and examined to illustrate publication trends over time. Figure 5 illustrates the yearly trend of research publications on multi-depot Vehicle Routing problems from 2016 to 2025. Data obtained from ScienceDirect database. Table 2 represents various research papers based on multi-depot and Single depot without time windows constraint. It shows different algorithms and benchmark datasets used by researchers. Also, Table 3 displays various research paper based on single and multi-depot with time windows constraint.Figure 6 represents the bibliometric coupling analysis of literature reviewed in this review article.

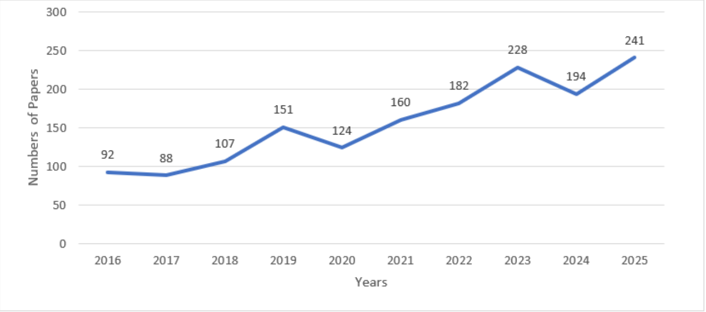


Figure 5: Research Publications from 2016-2025

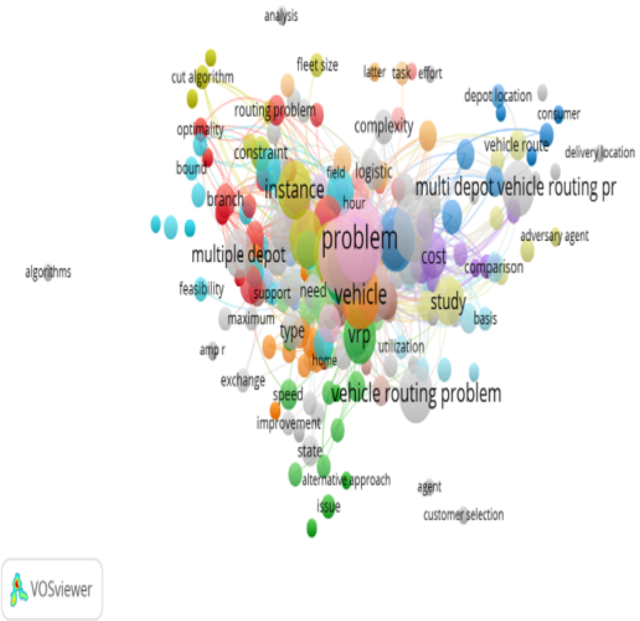


Figure 6: Bibliometric Coupling

Table 2: Without Time Windows Constraint

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Papers on Multi-Depot Vehicle Routing Problems					
Chavez et al. [5]	2016	Pareto-Based Ant Colony Optimization	Linehaul + Backhaul (Salhi and Nagy)	Environmental	Optimized backhaul routing
Oliveira et al. [7]	2016	Co-Operative Co-evolutionary	p01-p33(Cordeau et al.)	Economic	Reduced total route cost
Sundar and Rathinam [10]	2017	Mixed Integer Linear Programming (MILP)	TSPLIB (bays29, eil51-101), (bays29, eil51-101)	Economic	Optimal route optimization
Du et al. [11]	2017	Heuristic Algorithm	Real world (Beijing Company)	Environmental	Effective heuristic approach
Zhou et al. [13]	2018	Hybrid Metaheuristic Genetic Algorithm	Real world	Environmental	Effective hybrid Genetic Algorithm
Guedes et al. [14]	2018	Heuristic or Column Generation	Randomly generated, real world	Economic	Fast rescheduling solution
Lalang et al. [16]	2019	Integer Linear Programming	Self-Generated instances	Environment	Cost reduction achieved
Lalla-Ruiz et al. [18]	2020	POPMUSIC Algorithm	p01-p18, pr01-pr07 (Cordeau)	Economic	Arrival time minimization
Reyes-Rubiano et al. [20]	2020	Biased-Randomized Variable Neighbourhood search (BR-VNS)	p01-p23 (Chao et al., Vidal et al.)	Environmental + social	Sustainable routing optimization
Sadati et al. [22]	2020	Hybrid Algorithm	p01-p23 (Cordeau et al.)	Economic	Network disruption analysis
Barandao et al. [23]	2020	Memory-Based Iterated Local Search Algorithm	C, F, O, P, PR (Christofides et al.)	Economic	High competitiveness
Mora et al. [27]	2021	Mixed Integer Linear Programming (MILP)	Random/Cluster/ Geometric	Social/service-oriented	Delayed latency minimization
Kocaturk et al. [28]	2021	VNS-GRAMPS	p01, RC01, 01 (Cordeau et al.)	Economic	Reduced optimality gap
Wang et al. [29]	2021	Polygonal circumference + Hybrid Ant Colony Optimization	Real World	Economic	Enhanced operational efficiency
Uit et al. [31]	2021	Branch-Cut-Algorithm	A-MDTSP-200-30-1 (Bektas et al.)	Economic	Significant optimality gap reduction
Hasanpour jesri et al. [37]	2022	Mixed Integer Programming (MIP)	Synthetic Instances	Environmental	Significant cost reduction

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Abu-Monshar et al. [38]	2022	Messaging Protocol-Based Heuristic Optimization	p01, RC01, pro1 (Cordeau et al.)	Economic	Reduced vehicle utilization
Drew scott et al. [39]	2022	Mathematical Algorithm	TSPLIB and Random instances	Economic	High-quality scalable solution
Sahin et al. [40]	2022	Branch and Price	C,R,RC instances (Modified Solomon (1987))	Economic	Efficient exact solution method
Gu et al. [41]	2022	Artificial Bee Colony	R, C, RC (Christofides & Eilon)	Economic	Superior algorithm performance
Khodashenas et al. [44]	2023	Metaheuristics Algorithm	Self-generated	Economic	Balanced multi-objective optimization
Chen et al. [46]	2023	Dual Genetic Algorithm	p01 (Cordeau et al.)	Environmental	Total cost optimization
Zhang et al. [51]	2024	Improved Adaptive Large Neighborhood Search (IALNS)	C101, R101, RC101 type (Modified Solomon)	Environmental	Carbon emission reduction
Jolfaei et al. [52]	2024	Hybrid ELS-LNS algorithm	p01a-p10b (Cordeau et al. (2004))	Economic	Improved benchmark solution with efficient large-scale performance
Li Junjie et al. [53]	2024	Deep Reinforcement learning	p01-p11(Renaud et al.)	Economic	Superior performance
Diao et al. [56]	2024	Heuristic Algorithm, MIP	Synthetic dataset	Environmental	Cost-efficient coordinated routing
Li Jun Fan [57]	2024	Two Stage Hybrid Ant-Colony Algorithm	(R, C, RC) Modified Solomon	Environmental	Reduced costs and emissions
Yu et al. [58]	2024	Simulated Annealing	(R, C, RC) Modified Solomon	Environmental	High-quality solutions
Kumar et al. [59]	2024	Heuristic Algorithm	Random generated	Economic	Near-optimal travel times
Rajagukguk et al. [63]	2025	Mathematical optimization model	Self-defined	Economic	Reduced distribution costs
Kraiem et al. [64]	2025	Integer Linear Programming	pr06 (Cordeau 2005)	Computational & operational	Saving travel time
Cavecchia et al. [65]	2025	Adapted BSTG Algorithm	Real world	Computational & operational	Reduced total routing cost
Haslinger et al. [66]	2025	Exact Methods	Real world	Environmental	Optimized fleet size and energy efficiency
Tasdemir et al. [68]	2025	Stochastic programming	E-n51-k5 (Christofides)	Environmental	Minimize computational time
Jeong et al. [70]	2025	Approximate Message Passing Routing	Randomly generated	Operational	Near-optimal solutions with high computational efficiency

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Papers on Single Depot Vehicle Routing Problems					
Cueto et al. [26]	2021	Exact method	Real world	Economic	Robust and cost-effective solutions
Sluijk et al. [49]	2023	Multi-Labed algorithm with column generation	Cb-type (Dellaert et al.)	Environment & Economic	Guaranteed route feasibility
Ru et al. [60]	2024	Tabu search	Real-world (NS-GIM, High D)	Environment & Economic	Improved efficiency, higher profit
Zhang et al. [73]	2025	Local search algorithm	B-Y, Shanghai, SD	Economic	Significant reduction in the number of required vehicles
Fernandez Gil et al. [74]	2025	Relax and greedy search algorithm	Modified PRPLIB (Kramer et al. 2025)	Environment	Reduced fuel consumption and carbon emissions
Akkerman & Mes [76]	2025	Regression-based distance approximation	R, C, RC-stylized + Amsterdom case study	Environment & Economic	Up to 17% distance reduction

Table 3: With Time Windows Constraint

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Papers on Multi-Depots Vehicle Routing Problems					
Li et al. [6]	2016	Adaptive local Search (ALS)	pro01-pro18 (Cordeau et al.)	Economic	Reduce total cost
Bae and Moon [8]	2016	Mixed Integer Programming	1a-10b (Cordeau et al.)	Economic	Cost minimization
Mirabi et al. [9]	2016	Hybrid Genetic Algorithm	p01-p20 (Cordeau et al. (1999))	Economic	Effective Genetic algorithm clustering
Paz et al. [12]	2018	Mathematical Model	R, C, RC (Modified Solomon)	Economic	Optimized charging network, improved system efficiency
Rabbani [15]	2018	GA+HGA	Randomly Generated	Economic	Hybrid Genetic Algorithm Superiority
Wang et al. [17]	2019	Hybrid Genetic Algorithm	p01 (Christofides & Eilon)	Environmental	Reduced carbon emissions, cost-effective green routing
Olariu et al. [19]	2020	Heuristic Algorithm	m4n500-m4n1500 and m8n500-m8n1500(Huisman et al.)	Economic	Cost minimization achieved
Dridi et al. [21]	2020	Particle Swarm Optimization (PSO)	LC, LR, LRC (Li & Lim (2003))	Economic	Improved PSO performance
Lim et al. [25]	2021	Mixed integer programming	p01-p20(Eilon et al.1969, VRPLIB)	Economic	Benefits of splits-delivery

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Ghobadi et al. [30]	2021	Hybrid VNS-SA	R, C, RC (Modified Solomon)	Environment	Superior hybrid performance
Fan et al. [32]	2021	HGAVNS	C, R, RC, F, PR (Christofides et al.)	Environment	Total cost minimization
Rabbani [33]	2021	MINLP (Multi -Objective Mixed Integer Non-Linear Programming	Real-world (Iran Company)	Economic + social sustainability	Cost minimization with fairness
Bouyahyiouy et al. [36]	2022	Mixed Integer Programming (MIP)	R, C, RC (Modified Solomon)	Economical	Profit maximization efficiency
Kabadurmus et al. [43]	2023	Genetic Algorithm or Mixed Integer Linear Programming	Standard CVRP benchmark Sets (A, B and P) from Augerat et al. (1995)	Environmental	Carbon emission minimization
Bezerra et al. [45]	2023	SGVNSALS	R, C, RC (Modified Solomon)	Economic	Significant fleet reduction
Siping xue et al. [47]	2023	Adaptive Ant Colony Optimization	C, R, RC (Modified Solomon)	Economic	Cost saving with crowdsourcing
Wan et al. [50]	2023	Hybrid ant colony optimization algorithm	Synthetic/Real world	Environment	Improved optimal solutions
Yuksel et al. [54]	2024	Mixed Integer Programming	Modified 50-node Song	Social/Operational	Reduced distribution time
Londono et al. [55]	2024	Chu-Beasley algorithm	po1-p12, pr01-pro8 (Cordeau et al. (1997))	Environmental	Balanced and cost-efficient routing
Saxena et al. [62]	2025	Graph Neural Network or Greedy Optimization Algorithm	Extended T-drive data Set (Beijing) Yuan et al. 2010	Environmental	Lower fuel consumption
Haoyuan lv et al. [67]	2025	Multi-Tasking Ant System	p01-RC101 (Modified Solomon)	Economic/ operational	Improved routing efficiency through knowledge sharing
Xu et al. [69]	2025	Heuristic Methods Dynamic Programming Method	Real world	Environmental	23% cost saving through centralized planning
Guezouli et al. [72]	2025	C, R, RC (Cordeau et al.)	Real world	Environmental	Significant reduction in transportation
Acar et al. [79]	2025	Mixed Integer Model	Synthetic Medication Delivery Instances	Social & Operational	Efficiency and timely medication delivery
Papers on Single Depot Vehicle Routing Problems					
Dantzig & Ramser [1]	1959	Linear programming model	Classical VRP trial-based	Economic	Minimize travel distance
Mao et al. [24]	2020	Improved ACO with Local Search	Solomon-R, C, RC (Schneider et al.)	Environment	Cost reduction
Niu et al. [34]	2021	Improved Learnable Evolution model	R, C, RC (Solomon)	Economic	Superior Pareto performance

Author/s	Year	Algorithm/s	Benchmark datasets	Sustainability	Outcomes
Rajabi-Bahaabadi et al. [35]	2021	Hybrid Max-Min Ant colony system	R, C, RC (Solomon)	Economic	Improved routing realism
Yilmaz et al. [42]	2022	Variable Neighborhood search, Modified Clarke & Wright Saving Algorithm	C, R, RC-type (Schneider instances)	Environmental	Efficient solution performance
Wang et al. [48]	2023	Combined Genetic Algorithm and A* search algorithm	R-type (modified Solomon)	Environmental	Improved optimal solutions
Bi et al. [61]	2024	Proactive infeasibility prevention (PIP) with Neural Network	Generated for TSPTW, TSPDL, GFACTS	Economic	Fewer infeasible solutions
Mehmet Anil Akbay & Christian Blum [71]	2025	Akbay and Blum (2025)	C, R, RC (Modified Schneider)	Environment	Comprehensive benchmark dataSet for realistic 2E-EVRP testing
Tanash & As'ad [75]	2025	GRASP + PBACO + VNS	CR101-type (Modified Solomon)	Economic	High-quality solutions with minimal cost deviation
Fernandez-Gil et al. [77]	2025	Relax and Greedy Search Algorithm	PRPLIB, UK-type (Kramer et al.)	Environmental	Reduced fuel consumption and carbon emission
Jeong et al. [78]	2025	Q-learning + Pruning technique	Real-world case study (Seoul Metro Line -3)	Environmental	Reduced delivery times and operational

3. Mathematical Model (MDVRP)

A Multi-Depot Vehicle Routing Problem works on a mathematical model that was developed by Lim et al. (2021) [25] having assumption and several constraints. In a network, there are C customers with known demands D_i $(i = 1, \ldots, C)$, and K depots, each of which has V_k $(k = C+1, \ldots, C+K)$ vehicles. All vehicles may have homogeneous or heterogeneous capacities.

The mathematical model is summarized as follows:

- Each vehicle must begin and end its route at a single assigned depot.
- Customer demand must be satisfied.
- Vehicles capacities are known.
- Vehicles loading capacity must not exceeded.
- All customers and depot locations known in advance.
- The distances between all pairs of locations are predefined.

The definitions of constants, Sets, and variables used in the MIP formulation are given as follows.

Sets:

S_C= Set of customers

S_K= Set of depots

S = Set of all customers and depots

S_{V_k}= Set of all vehicle at depot k

Parameters:

C= Number of customers

K= Number of depots

L= Number of customers and depot

V_k= Number of vehicles at depot k

D_i= Demand of customer i $(1 \leq i \leq C)$

P_{kv}= Capacity of vehicles v from depot k

d_{ij} = Distance between nodes i and j
M=Maximum number of visits to a customer
B=A large number
Decision Variables:
U_{jkv}= Unloaded amount by vehicle v from depot k at customer j, where $1 \leq j \leq C$
$x_{ijkv} = 1$, if vehicle v from depot k travels from node i to j, where $v \in S_{V_k};$ 0, otherwise.
y_{ikv}= auxiliary variable for sub-tour elimination
Objective Function:

$$\min \sum_{i=1}^{L} \sum_{j=1}^{L} \sum_{m=1}^{K} \sum_{v=1}^{V_k} d_{ij}\, x_{ijkv} \tag{i}$$

Subject to

$$x_{ijkv} = 0,\ \forall i \neq j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{ii}$$

$$\sum_{i=1}^{L} x_{ijkv} = \sum_{i=1}^{L} x_{jikv},\ \forall j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{iii}$$

$$\sum_{v=1}^{V_k} \sum_{k=1}^{K} \sum_{i=1}^{L} x_{ijkv} \leq M,\ \forall j \in S_C \tag{iv}$$

$$\sum_{i=1}^{L} x_{iikv} = 0,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{v}$$

$$B \sum_{i=1}^{L} x_{iikv} \geq U_{jkv},\ \forall j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{vi}$$

$$x_{iikv} \leq U_{jkv},\ \forall i, j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{vii}$$

$$\sum_{v=1}^{V_k} \sum_{k=1}^{K} U_{jkv} = D_j,\ \forall j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{viii}$$

$$\sum_{j=1}^{C} U_{jkv} \leq P_{kv},\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{ix}$$

$$y_{ikv} - y_{jkv} + L\, x_{ijkv} \leq L - 1,\ \forall i \neq j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{x}$$

$$x_{ijkv} \in \{0, 1\},\ \forall i, j \in S_C,\ \forall k \in S_K,\ \forall v \in S_{V_k} \tag{xi}$$

$$y_{jkv} > 0, \text{ integer}, \ \forall j \in S_C, \ \forall k \in S_K, \ \forall v \in S_{V_k} \quad \text{(xii)}$$

Equation (i) represents the objective function of this model which is to minimize the total travelled distance by all vehicles to all customers. Constraint (ii) means each vehicle starts from its origin depot and return same depot. Constraint (iii) ensures that if vehicle comes to a location, it must also leave this place. Constraint (iv) means each customer node can be visited by up to M vehicles to satisfy customer demand. Constraint (v) ensures that prevents the formulation of loops of any route at a node. equations (vi) and (vii) ensure that if vehicle v from depot m travels from node i to j, the vehicle should unload U_{jkv} at a customer node j should be the same as its demand. Equation (viii) guarantees that sum of the unloaded quantity at a client's node j should be the as its demands. constraint (ix) ensures that the total unloaded amounts by each vehicle on its route remains within the vehicle's capacity. Condition (x) says that sub-tour elimination. Constraints (xi) and (xii) talk about nature of binary and integer constraints. The main constraints needed to resolve the problem are included in the proposed mathematical model. To enhance a few other additional constraints identified in the literature are also further investigated and discussed separately.
In the MDVRP, various types of constraints are introduced to ensure that the routing and delivery process remains feasible, and practically applicable. These constraints are essential because they define the limits that the optimization model must work inside. Figure 7 given reveals the types of different constraints.

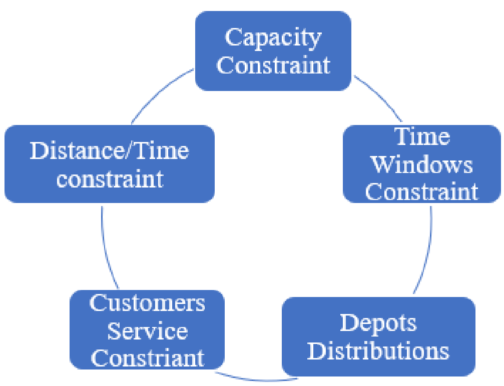


Figure 7: Types of different constraints

3.1. Capacity Constraint

In this constraint, each vehicle has fixed capacity. Vehicle capacity constraint ensures that each vehicle fulfil demands of customers without exceeding its limit [40]. If customers demand is extra, then additional vehicles are required on these routes. In this review paper 65 papers based on capacity constraint and 11 papers based on non-capacity constraint shown in Figure 8 and capacity constraint is written in the form of equation (xiii) and the parameters used are:

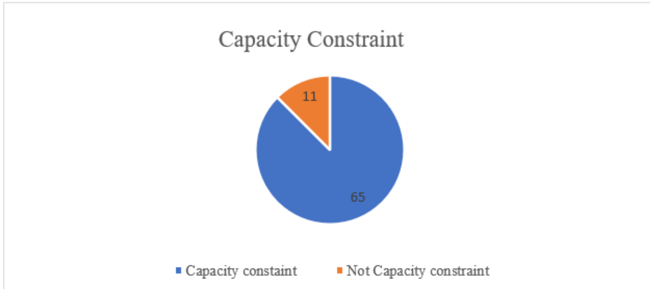


Figure 8: Capacity Constraint

$$\sum_{p\in N}\sum_{q\in C} d_q\, x_{pqv} \leq Q_v, \quad \forall v \in V \tag{xiii}$$

d_q = Demand of customer q
Q_v = Maximum load Capacity of vehicle v
x_{pqv} = Routing Variable
$p, q \in N$ = Set of all nodes
C = Set of customers
V = Set of vehicles

3.2. Time windows Constraint

The Time Windows Constraints means delivery to the customers must be in specific time period for example customer mentions the time slot during the order then vehicle reaches customer location during this slot [42]. In this review, 40 papers based on without time-window and 35 papers focusing with time window constraints. The time windows constraint shown in Figure **??** is given below. Time Window Constraint written in the form of equation (xiv) and the parameters are used are:

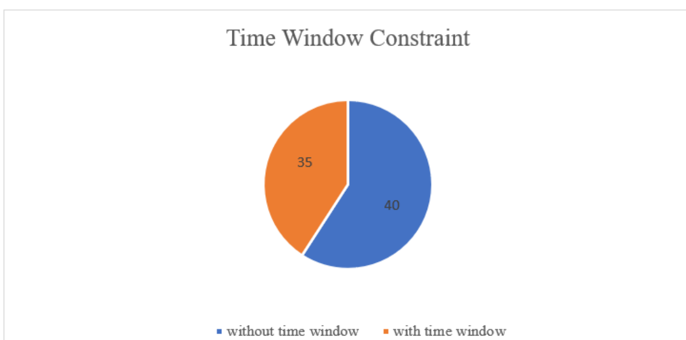


Figure 9: Time Window Constraint

$$r_{tm} = srt \cdot \max(sm - \hat{d}m, 0) + urt \cdot \max(\hat{d}m - um, 0), \quad \forall m \in C \tag{xiv}$$

Where, srt,urt= A unit penalty cost is applied for each hour before and after arrivals relative to given time window constraint.
sm,um= Time window for a customer node.
dm = The arrival time of vehicle at customer m.
r_{tm} = punishment cost for not delivering the goods in given time window.

3.3. Depots Distributions

Depots distribution constraint ensures that each vehicle starts and ends its route at assigned depot [43]. In this review paper 59 papers are related to multi-depot and 17 papers for single depot with one review paper of single depot. Figure 10 represents single and multiple depot distribution is given below and equation (xv) represents the depots distribution and the parameters used are:
C= Set of customers
D =Set of depots
V_d= Set of vehicles available at depot d
$S_V k$= Set of all vehicles at depot k
x_{dqv},x_{pdv} = binary routing variables
Multi-Depot Constraint written in the form as:

$$\begin{cases} \sum_{q\in C} x_{dqv} \leq 1, & \forall d \in D, \forall v \in V_d \\ \sum_{p\in C} x_{pdv} \leq 1, & \forall d \in D, \forall v \in V_d \end{cases} \tag{xv}$$

$$x_{dqv} = \begin{cases} 1, & \text{if vehicle } v \text{ from depot } d \text{ travels to customer } q, \\ 0, & \text{otherwise.} \end{cases}$$

$$x_{pdv} = \begin{cases} 1, & \text{if vehicle } v \text{ from depot } p \text{ travels to customer } d, \\ 0, & \text{otherwise.} \end{cases}$$

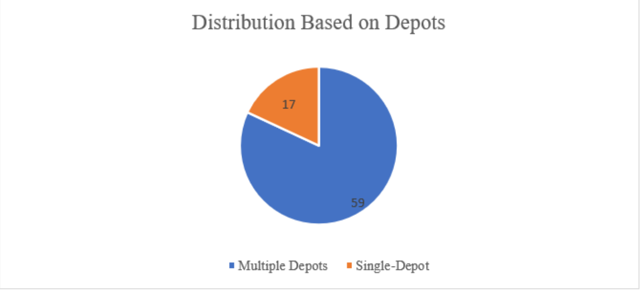


Figure 10: Distribution based on the number of depots

3.4. Open/Closed VRP Constraint

In open VRP, each vehicle starts routs from its assigned depot and after completing deliveries vehicles does not need to return same depot or any depot [6]. In Closed VRP, each vehicle starts routes from its assigned and after completing deliveries vehicles return to same depot. In this review article 63 papers based on Closed Vehicle Routing Problem, 12 papers based on Open Vehicle Routing Problem and 1 paper is based on both Closed and Open VRP model shown in Figure 11 is given below and equation (xvi) represents closed VRP and the parameters used are:

$$\sum_{q\in C} x_{dqv} = \sum_{p\in C} x_{pdv}, \quad \forall d \in D, \forall v \in V_d \tag{xvi}$$

C= Set of customers
D =Set of depots
V_d= Set of vehicles available at depot d
x_{dqv},x_{pdv} = binary routing variables

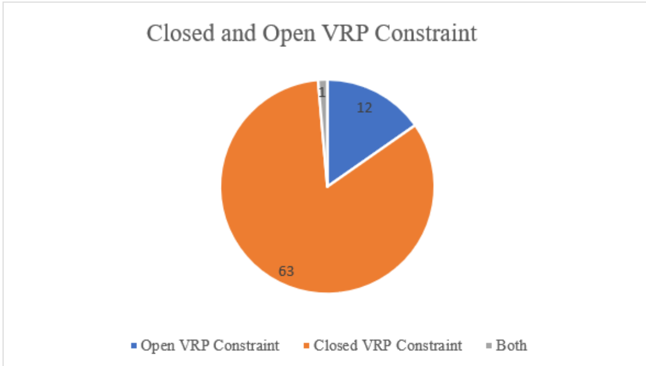


Figure 11: Based On Closed and Open VRP constraint

4. Solution Approaches

labelsec4 Multi-Depot Vehicle Routing Problems cannot be solved manually because its complexity as there are different types of constraints and conditions that make them NP Hard problems that are hard to solve. Different solution approaches have been developed over the years to deal with the challenges of multi-depot vehicle routing problems (MDVRP). These methods focus primarily on finding efficient routes, reducing total travel costs, and improving the overall performance of logistics networks. Exact methods, such as mixed-integer programming and branch-and-bound, are commonly used for small or medium-sized problems because they provide and accurate results but large problem take too much expensive computational time. To solve larger and NP-hard problems, researchers have moved to heuristic methods like the savings and sweep algorithms, which deliver good results in less time. In modern times metaheuristic techniques such as Genetic Algorithm, Tabu Search, Particle Swarm Optimization, Ant colony Optimization have become very popular and give prefect solution. These approaches are flexible and can handle complex problems, real-life routing situation efficiently. Moreover, hybrid approaches that combine two or more techniques have been broadly applied to improve solution quality and speed. From 2016 to 2025, research in multiple-depot routing has moved from traditional models toward smarter and highly adaptive systems. Numerous recent studies use hybrid metaheuristics, machine learning support, and multi-objective optimization to address issues like time windows, demand changes, and environment goals. This indicates a clear trend toward intelligent and combined solutions for modern logistics networks.

MDVRP cannot be solved analytically because of their complexity as their various conditions and constraints that make them NP Hard problems that are difficult to solve.

Complexity Classes: According to Bovet et al. (1992) [3] complexity class comprises decision problems solvable by algorithmic methods. Time and space are two main resources in complexity classes.

Time complexity: According to Hartmanis J et al. (1971) [2] within computer science theory, quantifies the amount of time an algorithm to solve a given problem. It is denoted by Big O notation, $O(n)$, $O(n \log n)$, $O(n\alpha)$, $O(2^n)$, where n is unit in size of bits represented the inputs.

Polynomial Time: polynomial time is described by Hartmanis J et al. (1971) [2]. In polynomial time running time of an algorithm is upper bounded by a polynomial function of the input size. Polynomial time is denoted by $T(n) = O(n^k)$ where n is complexity input and k is +ve constant.

Exponential Time: Exponential time is described by Hartmanis J et al. (1971) [2]. In exponential time running time is upper bounded by $2^{\mathrm{poly}(n)}$, where $poly(n)$ is some polynomial in n.

Deterministic Algorithm: According to Delimata P et al. (2010) [4], a deterministic algorithm consistently produces the same output for a given input, since the machine follows the same sequence of states. Different type of algorithm deterministic algorithm is commonly studied and familiar type of algorithm.

Non-Deterministic Algorithm: A nondeterministic algorithm [4] is an algorithm in which the same input can lead to different output in different runs.

Now, the various type of complexity classes is presented below:

In Figure 12 it can easily see complexity class P lies in complexity class NP.

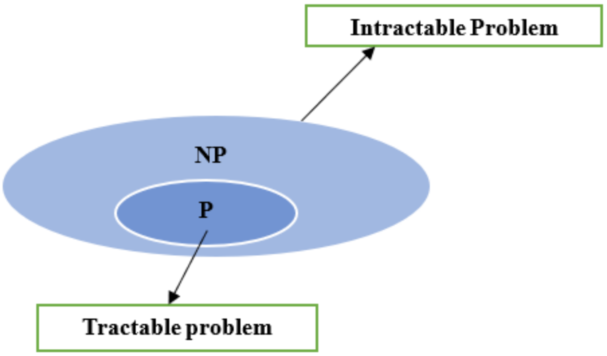


Figure 12: P and NP Problems

P Class Problem: The complexity class P includes the set of decision problems that can be solved in polynomial time by deterministic algorithms within polynomial time bounds. According to Cobham's (1965) states that the class P consists of computational problems that are efficiently solvable.
NP Class Problem: NP (non-deterministic polynomial time) class problems are computational problems for which candidate solution can be solved in polynomial time by a deterministic Turing machine.
NP-Hard Complexity class: Gu et al. (2022) said that NP-Hard is a class of problems that are very hard to solve. These problems are at least as difficult as the hardest problems in NP. Unlike NP-Complete problems, NP-Hard problems do not need to belong to the NP, which means their solutions may not be easy to verify. If single one NP-Hard problem is solved in polynomial time, then every NP problem can also be solved in polynomial time. In others words, NP-Hard problems are very challenging problems, and their solutions may not easy or fast to verify.
NP-Complete Complexity Class: NP-Complete classes of problems that are hard to solve, but easy to verify. This means finding the solution can take a lot of time, but if a solution is given, we can verify fast whether it is correct. NP-Complete problems fall under the NP class and are also the difficult problems in NP. In other words, NP-Complete problems are hard to solve, but easy to check. Figure 13 depicts the Venn diagram considering all the complexity classes and their relation with each other.

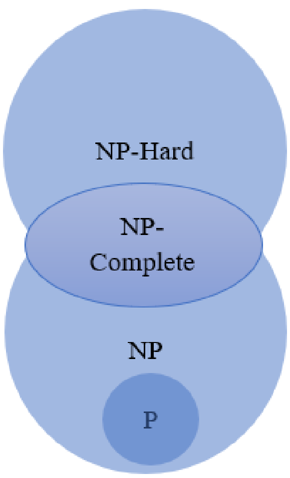


Figure 13: P, NP, NP-Hard, NP-Complete Problems

5. Applications of Multi-Depot Vehicle Routing Problem

Real-life transportation and distribution systems deal with multi-depot routing problems. Multiple systems where vehicles start and serve clients are involved in these problems. Multiple depots enhance the capacity and productivity of such systems. The following part covers the different real-life uses for multi-depot routing.

Transportation and logistics play a very important role in global economy. It responsible for delivered goods from manufactures to warehouses, shops and finally end customers. As e-commerce, global demand for fast delivery, manging logistics has become more complex. One effective way to manage this complexity is multi-depot system, where multiple depots distribute goods to a large number of customers. In MDVRP, vehicles are assigned to different depots, serve all customers and usually return to same depot. Multi-Depot helps to minimize total travel time and fuel use. This system is commonly applied in transportation and logistics [63]. Multi-Depot system also helps in spread workload across various depots, which enhances overall efficiency. By placing depots near to important customer area, companies can provide quicker deliveries and enhance customer satisfaction.

Public services and municipal operations are a crucial part of everyday life of people living in urban and town areas. Such services cover various activities like garbage collection, street cleaning, snow clearing, water supply maintenance, road repair, upkeep of public lighting and emergency services. Municipal authorities use a multi-depot system to manage these services efficiently. In a Multi-Depot Vehicle Routing Problem also plays very important role in public service operations. MDVRP design the best route for garbage trucks so that waste can be collected easily and economically [69]. In MDVRP, multiple depots have different and multiple types of vehicles so that vehicles are required to cover maximum area while minimizing total operational costs. Similarly, in public transportation systems, MDVRP helps to design best route for buses, school transportation services and shuttle services which provides multiple routes under demand and time window constraints ensures better services and reduce operational costs.

Healthcare and medical distribution is very important service that directly influences people life. People need hospitals, pharmacies, clinics, blood banks and diagnostic centres to receive timely treatment and healthcare services. In health care and medical services. To ensure medical services smoothly and timely, an effective distribution system is required. MDVRP has become more significant due to reliable distribution of health care products. In this system, many depots located at different location to store and distribute medical supplies instead of a single central warehouse. MDVRP designs best delivery routes to help manage deliveries from multiple warehouses (depots) to hospitals and clinics [79]. It also optimizes routes of vehicles to ensure lower costs, timely delivery and also improves health care services. In normal and emergency situation, the multi-depot approach helps to provide effective and timely healthcare services to people.

In e-commerce and retail distributions, companies have several warehouses and plays a very important role in everyday life. Today, consumer buy a wide range of products through online platforms and retail outlets, such as groceries, electronics, medicines, clothing and household items. Customers expect quick delivery, cost effective and reliable service. To fulfil these expectations, e-commerce and retail companies use efficient logistics and delivery systems. Multi-depot system is most effective system used in this sector. MDVRP helps in designing the service of different depots to different customers. Online delivery companies like Amazon, Flipkart and Myntra use MDVRP algorithms to organize delivery routes for multiple vehicles to serve customers in different cities. MDVRP also helps e-commerce companies to deliver online orders from several warehouses to customers' home on specific time period and reducing delivery costs. MDVRP manage large numbers of orders, especially peak demands periods like festival days [51]. In the current highly competitive market, this approach plays an important role in the successful e-commerce and retail businesses.

Humanitarian and disaster relief operations focus on protect lives and help people during natural or human-made disasters. These types of disaster may include earthquakes, cyclones, floods, landslides, fires, tsunamis and conflicts. During this situations, people immediate need food, medicines, medical care, shelter and water. Multi-Depot system is very important role play most effective logistic approaches in humanitarian and disaster relief operation. The Multi-Depot Vehicle Routing Problem helps to find the best routes for most affected areas so that vehicles serve food, medicines, water supply and emergency equipment. In both quick response and long-term recovery phases, this approach is essential for successful disaster relief operations. Humanitarian organizations like NGOs, government agencies and international relief agencies widely adopt multi-depot systems. In conclusion, humanitarian and disaster relief operation is one of the most important applications of multi-depot systems [54]. In Figure 14, the applications of Multi-Depot Vehicle Routing Problems are shown in the form of a flow chart.

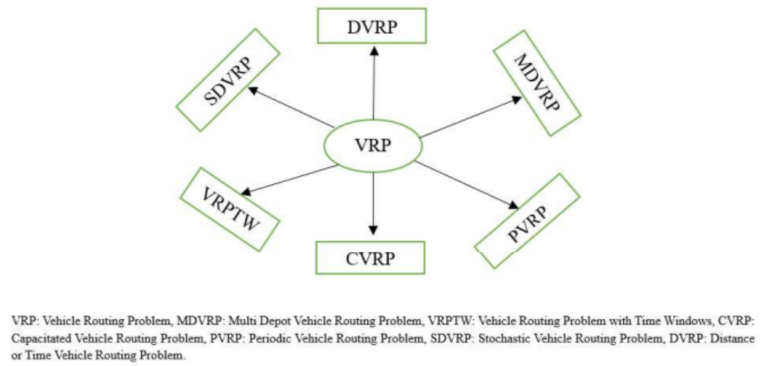


Figure 14: Applications of Multi-Depot Vehicle Routing Problem

6. Future Scope

In future, MDVRPs can be more focused on sustainable development as green vehicle routing problems and electric vehicle routing problems are related to the sustainability of environment. Green vehicles reduce fuel consumption, and carbon emissions. In future MDVRP can include green vehicles, charging constraints and emission-based objectives. MDVRP also include stochastics and uncertain demands. In real world, customer demands randomly change so MDVRP may include studies on random changes in demand. AI and Machine learning can play crucial role so that MDVRP used AI-based, adaptive algorithm and also include hybrid metaheuristic approaches. These methods can improve quality, solutions and computational time. Moreover, MDVRP methodologies that balance economic, environmental, and service- level criteria with more flexible outcomes. Finally, future studies should work on real-world, large scale MDVRP instances, including the applications related to urban logistics, multi-echelon supply chain, and e-commerce distribution, based on real life benchmark datasets.

7. Conclusion

This paper concludes that Multi depot and single depot VRP are significant areas of research. The studies include an in-depth examination of multi-depot vehicle routing problems and single depot vehicle routing problems has been given. This review has marked the complexities in VRPs and MDVRPs, such as long routes, sustainability, dynamic demands. In the previous years, most of the MDVRPs are solved by metaheuristic approaches (Genetic Algorithms, Ant Colony Optimization, Particle Swarm Optimization). In this review article, 42 research papers address study on VRP without time-window constraints, while 33 research articles studies on with time window constraints. Based on overall analysis, in this review paper different benchmarks were used across studies, which helped in comparing the results of the proposed models. In the past few years, main objective of the researchers is to minimize travel cost, distance and travel time. However, many problems are unsolved related to larger and complex problems and real-world situations like traffic condition, weather and customers random change in demands. By considering these challenges, in MDVRP hybrid metaheuristic approaches and standardised benchmarks can be used to compare the different solution approaches. MDVRP can also contribute in maintaining more sustainable environment in the urban areas. As in upcoming days, MDVRP is moving more towards the electrification, therefore, optimization routes are becoming more important to reduce CO_2 emissions.

In general, MDVRP remains a consistently evolving field with strong potential to support efficient, economical and eco-friendly logistics operations.

References

1. Dantzig, G. B., & Ramser, J. H., *The truck dispatching problem*, Management science 6(1), 80-91, (1959) .
2. Hartmanis, J., & Hopcroft, J. E., *An overview of the theory of computational complexity*, Journal of the ACM (JACM),18(3),444-475, (1971).
3. Bovet, D. P., Crescenzi, P., & Silvestri, R., *uniform approach to define complexity classes*, Theoretical Computer Science, 104(2), 263-283, (1992).
4. Delimata, P., Marszał-Paszek, B., Moshkov, M., Paszek, P., Skowron, A., & Suraj, Z., *Comparison of some classification algorithms based on deterministic and nondeterministic decision rules*, In Transactions on Rough Sets XII, 6190, 90-105, (2010).
5. Chávez, J. J., Escobar, J. W., & Echeverri, M. G., *A multi-objective Pareto ant colony algorithm for the Multi-Depot Vehicle Routing problem with Backhauls*, International Journal of Industrial Engineering Computations, 7(1), 35, (2016).
6. Li, J., Li, Y., & Pardalos, P. M., *Multi-depot vehicle routing problem with time windows under shared depot resources*, Journal of combinatorial optimization, 31(2), 515-532, (2016).
7. de Oliveira, F. B., Enayatifar, R., Sadaei, H. J., Guimarães, F. G., & Potvin, J. Y., *A cooperative coevolutionary algorithm for the multi-depot vehicle routing problem*, Expert Systems with Applications, 43, 117-130, (2016).
8. Bae, H., & Moon, I., *Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles*, Applied Mathematical Modelling, 40(13-14), 6536-6549, (2016).
9. Mirabi, M., Shokri, N., & Sadeghieh, A., *Modeling and solving the multi-depot vehicle routing problem with time window by considering the flexible end depot in each route*, International Journal of Supply and Operations Management, 3(3), 1373, (2016).
10. Sundar, K., & Rathinam, S., *Algorithms for heterogeneous, multiple depots, multiple unmanned vehicle path planning problems*, Journal of Intelligent & Robotic Systems, 88(2), 513-526, (2017).
11. , J., Li, X., Yu, L., Dan, R., & Zhou, J., *Multi-depot vehicle routing problem for hazardous materials transportation: A fuzzy bilevel programming*, Information sciences, 399, 201-218, (2017).
12. Paz, J., Granada-Echeverri, M., & Escobar, J., *The multi-depot electric vehicle location routing problem with time windows*, International journal of industrial engineering computations, 9(1), 123-136, (2018).
13. Zhou, L., Baldacci, R., Vigo, D., & Wang, X., *A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution*, European Journal of Operational Research, 265(2), 765-778, (2018).
14. Guedes, P. C., & Borenstein, D., *Real-time multi-depot vehicle type rescheduling problem*,Transportation Research Part B: Methodological, 108, 217-234, (2018).
15. Rabbani, M., Pourreza, P., Farrokhi-Asl, H., & Nouri, N, *A hybrid genetic algorithm for multi-depot vehicle routing problem with considering time window repair and pick-up*, Journal of Modelling in Management, 13(3), 698-717, (2018).
16. Wang, Y., Assogba, K., Fan, J., Xu, M., Liu, Y., & Wang, H., *Modulating the multi-depot vehicle routing problem model with time windows using occasional driver*,International Journal of Innovation Creativity and Change, 5(3), 39-60, (2019).
17. Lalang, D., Making, S. R. M., & Manapa, I. Y. H., *Multi-depot green vehicle routing problem with shared transportation resource: Integration of time-dependent speed and piecewise penalty cost*,Journal of Cleaner Production, 232, 12-29, (2019).
18. Lalla-Ruiz, E., & Voß, S., *A popmusic approach for the multi-depot cumulative capacitated vehicle routing problem*,Optimization Letters, 14(3), 671-691, (2020).
19. Olariu, E. F., & Frăsinaru, C., *Multiple-depot vehicle scheduling problem heuristics*,Procedia Computer Science, 176, 241-250, (2020).
20. Reyes-Rubiano, L., Calvet, L., Juan, A. A., Faulin, J., & Bové, L., *A biased-randomized variable neighborhood search for sustainable multi-depot vehicle routing problems*,Journal of Heuristics, 26(3), 401-422, (2020).
21. Harbaoui Dridi, I., Ben Alaïa, E., Borne, P., & Bouchriha, H., *Optimisation of the multi-depots pick-up and delivery problems with time windows and multi-vehicles using PSO algorithm*,International Journal of Production Research, 58(14), 4201-4214, (2020).
22. Sadati, M. E. H., Aksen, D.,& Aras, N., *The r-interdiction selective multi-depot vehicle routing problem*,International transactions in operational research, 27(2), 835-866, (2020).
23. Brandão, J., *A memory-based iterated local search algorithm for the multi-depot open vehicle routing problem*,European Journal of Operational Research, 284(2), 559-571, (2020).

24. Mao, H., Shi, J., Zhou, Y., & Zhang, G., *The electric vehicle routing problem with time windows and multiple recharging options*, IEEE Access, 8, 114864-114875, (2020).

25. Lim, H., Lee, G. M., & Singgih, I. K., *Multi-depot split-delivery vehicle routing problem*, IEEE Access, 9, 112206-112220, (2021).

26. Fermin Cueto, P., Gjeroska, I., Sola Vilalta, A., & Anjos, M. F., *A solution approach for multi-trip vehicle routing problems with time windows, fleet sizing, and depot location*, Networks, 78(4), 503-522, (2021).

27. Osorio-Mora, A., Soto-Bustos, M., Gatica, G., Palominos, P., & Linfati, R., *The multi-depot cumulative vehicle routing problem with mandatory visit times and minimum delayed latency*, IEEE Access, 9, 27210-27225, (2021).

28. Kocatürk, F., Tütüncü, G. Y., & Salhi, S., *The multi-depot heterogeneous VRP with backhauls: formulation and a hybrid VNS with GRAMPS meta-heuristic approach*, Annals of Operations Research, 307(1), 277-302, (2021).

29. Wang, Y., Wang, X., Guan, X., & Tang, J., *Multi-depot recycling vehicle routing problem with resource sharing and time window assignment*, Journal of Advanced Transportation, 2021(1), 2327504, (2021).

30. Ghobadi, A., Tavakkoli Moghadam, R., Fallah, M., & Kazemipoor, H., *Multi-depot electric vehicle routing problem with fuzzy time windows and pickup/delivery constraints*, Journal of applied research on industrial engineering, 8(1), 1-18, (2021).

31. Uit het Broek, M. A., Schrotenboer, A. H., Jargalsaikhan, B., Roodbergen, K. J., & Coelho, L. C., *Asymmetric multi-depot vehicle routing problems: Valid inequalities and a branch-and-cut algorithm*, Operations Research, 69(2), 380-409, (2021).

32. Fan, H., Zhang, Y., Tian, P., Lv, Y., & Fan, H., *Time-dependent multi-depot green vehicle routing problem with time windows considering temporal-spatial distance*, Computers & Operations Research, 129, 105211, (2021).

33. Rabbani, M., Akbarpour, M., Hosseini, M., & Farrokhi-Asl, H., *A Multi-depot Vehicle Routing Problem with Time Windows and Load Balancing: A Real-World Application*, International Journal of Supply & Operations Management,8(3), 347-369, (2021).

34. Niu, Y., Kong, D., Wen, R., Cao, Z., & Xiao, J., *An improved learnable evolution model for solving multi-objective vehicle routing problem with stochastic demand*, Knowledge-Based Systems, 230, 107378, (2021).

35. Rajabi-Bahaabadi, M., Shariat-Mohaymany, A., Babaei, M., & Vigo, D., *Reliable vehicle routing problem in stochastic networks with correlated travel times*, Operational Research, 21(1), 299-330, (2021).

36. Bouyahyiouy, K. E., & Bellabdaoui, A. *The selective full truckload multi-depot vehicle routing problem with time windows: Formulation and a genetic algorithm*, International Journal of Supply and Operations Management, 9(3), 299-320, (2022).

37. Hasanpour Jesri, Z. S., Eshghi, K., Rafiee, M., & Van Woensel, T., *The multi-depot traveling purchaser problem with shared resources*, Sustainability, 14(16), 10190, (2022).

38. Abu-Monshar, A., Al-Bazi, A., & Palade, V., *An agent-based optimisation approach for vehicle routing problem with unique vehicle location and depot*, Expert Systems with Applications, 192, 116370, (2022).

39. Scott, D., Manyam, S. G., Casbeer, D. W., & Kumar, M., *A Lagrangian algorithm for multiple depots traveling salesman problem with revisit period constraints*, IEEE Transactions on Automation Science and Engineering, 20(1), 690-702, (2022).

40. Şahin, M. K., & Yaman, H., *A branch and price algorithm for the heterogeneous fleet multi-depot multi-trip vehicle routing problem with time windows*, Transportation Science, 56(6), 1636-1657, (2022).

41. Gu, Z., Zhu, Y., Wang, Y., Du, X., Guizani, M., & Tian, Z., *Applying artificial bee colony algorithm to the multidepot vehicle routing problem*, Software: Practice and Experience, 52(3), 756-771, (2022).

42. Yilmaz, Y., & Kalayci, C. B., *Variable neighborhood search algorithms to solve the electric vehicle routing problem with simultaneous pickup and delivery*, Mathematics, 10(17), 3108, (2022).

43. Kabadurmus, O., & Erdogan, M. S., *A green vehicle routing problem with multi-depot, multi-tour, heterogeneous fleet and split deliveries: a mathematical model and heuristic approach*, Journal of Combinatorial Optimization, 45(3), 89, (2023).

44. Khodashenas, M., Najafi, S. E., Kazemipoor, H., & Sobhani, M., *Providing an integrated multi-depot vehicle routing problem model with simultaneous pickup and delivery and package layout under uncertainty with fuzzy-robust box optimization method*, Decision Making: Applications in Management and Engineering, 6(2), 372-403, (2023).

45. Bezerra, S. N., Souza, M. J. F., & de Souza, S. R., *A variable neighborhood search-based algorithm with adaptive local search for the vehicle routing problem with time windows and multi-depots aiming for vehicle fleet reduction*, Computers & operations research, 149, 106016, (2023).

46. Chen, C. M., Lv, S., Ning, J., & Wu, J. M. T., *A genetic algorithm for the waitable time-varying multi-depot green vehicle routing problem*, Sustainable Operations and Computers, 15(1), 124, (2023).

47. Xue, S., *An adaptive ant colony algorithm for crowdsourcing multi-depot vehicle routing problem with time windows*, Symmetry, 4, 62-75, (2023).

48. Wang, D. L., Ding, A., Chen, G. L., & Zhang, L., *A combined genetic algorithm and A* search algorithm for the electric vehicle routing problem with time windows*, Advances in Production Engineering & Management, 18(4), 403-416, (2023).

49. Sluijk, N., Florio, A. M., Kinable, J., Dellaert, N., & Van Woensel, T., *A chance-constrained two-echelon vehicle routing problem with stochastic demands*, Transportation Science, 57(1), 252-272, (2023).

50. Wan, F., Guo, H., Pan, W., Hou, J., & Chen, S., *A mathematical method for solving multi-depot vehicle routing problem: F. wan et al.*, Soft Computing, 27(21), 15699-15717 (2023).

51. Zhang, M., Chen, A., Zhao, Z., & Huang, G. Q., *A multi-depot pollution routing problem with time windows in e-commerce logistics coordination*, Industrial Management & Data Systems, 124(1), 85-119, (2024).

52. Jolfaei, A. A., & Alinaghian, M., *Multi-depot vehicle routing problem with roaming delivery locations considering hard time windows: Solved by a hybrid ELS-LNS algorithm*, Expert Systems with Applications, 255, 124608, (2024).

53. Li, J., Dai, B. T., Niu, Y., Xiao, J., & Wu, Y., *Multi-type attention for solving multi-depot vehicle routing problems*, IEEE Transactions on Intelligent Transportation Systems, 25(11), 17831-17840, (2024).

54. Yüksel, Z., Epcim, D. E., & Mete, S., *Multi-Depot vehicle routing problem with drone collaboration in humanitarian logistic*, Journal of Optimization and Decision Making, 3(1), 438-448, (2024).

55. Londono, A. A., Gonzalez, W. G., Giraldo, O., Escobar, J., Ozaki, M., Adachi, Y., ... & Ishii, N., *A hybrid heuristic approach for the multi-objective multi depot vehicle routing problem*, International Journal of Industrial Engineering Computations, 15, 337-354, (2024).

56. Diao, X., Fan, H., Zhu, X., & Liu, Z., *Multi-depot routing problem with van-based driverless vehicles*, Scientific Reports, 14(1), 19807, (2024).

57. Fan, L., *A two-stage hybrid ant colony algorithm for multi-depot half-open time-dependent electric vehicle routing problem*, Complex & Intelligent Systems, 10(2), 2107-2128, (2024).

58. Yu, V. F., Lin, S. W., Zhou, L., & Baldacci, R., *A fast simulated annealing heuristic for the multi-depot two-echelon vehicle routing problem with delivery options*, Transportation Letters, 16(8), 921-932, (2024).

59. Kumar, D. P., Rathinam, S., Darbha, S., & Bihl, T, *Heuristic for min-max heterogeneous multi-vehicle multi-depot traveling salesman problem*, AIAA SCITECH 2024 Forum, 0234, (2024).

60. Ru, S., *Vehicle logistics intermodal route optimization based on Tabu search algorithm*, Scientific reports, 14(1), 11859, (2024).

61. Bi, J., Ma, Y., Zhou, J., Song, W., Cao, Z., Wu, Y., & Zhang, J., *Learning to handle complex constraints for vehicle routing problems*, Advances in Neural Information Processing Systems, 37, 93479-93509, (2024).

62. Saxena, D., Singh, N., Gupta, K., Verma, A., Mishra, V., Kumar, J., ... & Singh, A. K., *An Intelligent Multi-Depot Vehicle Routing and Management Model for Smart Cities*IEEE Transactions on Intelligent Transportation Systems, 26(6), 7740-7754, (2024).

63. Rajagukguk, A. M., Nababan, E. S. M., & Gultom, P., *Logistics distribution optimization model using multi-depot capacitated vehicle routing problem*, Jurnal Matematika, 8(2), 215-224, (2025).

64. Kraiem, A., Audy, J. F., & Lamghari, A., *Mixed integer linear programming model for a multi-depot arc routing problem with different arc types and flexible assignment of end depot*, Transportation Research Procedia, 82, 1109-1119, (2025).

65. Cavecchia, M., de Queiroz, T. A., Lancellotti, R., Zucchi, G., & Iori, M., *A Real-World Multi-Depot, Multi-Period, and Multi-Trip Vehicle Routing Problem with Time Windows*, In ICORES, 112-122, (2025).

66. Haslinger, X., Gaar, E., & Parragh, S. N., *An exact approach for the multi-depot electric vehicle scheduling problem*, arXiv:2504.13063, (2025).

67. Lv, H., Liu, R., & Li, J., *A multitasking ant system for multi-depot pick-up and delivery location routing problem with time window*, Complex & Intelligent Systems, 11(2), 159, (2025).

68. Taşdemir, B. D., & Özyörük, B., *Mathematical Model for Multi Depot Simultaneously Pick Up and Delivery Vehicle Routing Problem with Stochastic Pick-Up Demand*, Gazi University Journal of Science, 38(1), 219-235, (2025).

69. Xu, Y., Abdelaziz, F. B., Sahnoun, M. H., & Louis, A., *Optimized cooperative vehicle routing in multi-depot collection systems for circular economy: Model development and case study*, Journal of Cleaner Production, 486, 144417, (2025).

70. Jeong, B. M., Jang, D. S., & Choi, H. L., *Decentralized message passing algorithm for heterogeneous multi-depot vehicle routing problems*, Available at SSRN 5062181, (2025).

71. Akbay, M. A., & Blum, C., *A dataset for two-echelon electric vehicle routing problems*, Data in Brief, 60, 111470, (2025).

72. Guezouli, L., Guezouli, L., Ameghchouche, S., & Menzer, H., *Enhancing Green Vehicle Routing Efficiency Through Machine Learning-Optimized Genetic Algorithms*, International Journal of Networked and Distributed Computing, 13(1), 21, (2025).

73. Zhang, H., Li, Q., & Yao, X., *An efficient local search algorithm for split delivery vehicle routing problem with three-dimensional loading*, Memetic Computing, 17(2), 1-37, (2025).

74. Yernar, A., & Turan, C., *Recent developments in vehicle routing problem under time uncertainty: a comprehensive review*, Bulletin of Electrical Engineering and Informatics, 14(2), 1263-1275, (2025).

75. Tanash, M., & As'ad, R., *Heuristic Algorithms for the Heterogeneous Vehicle Routing Problem with Time Windows, Customers Priority, Pickup and Delivery*, IEEE Access, 13, 110605-110622, (2025).

76. Akkerman, F., & Mes, M., *Distance approximation to support customer selection in vehicle routing problems*, Annals of operations research, 350(1), 269-297, (2025).

77. Fernández Gil, A., Lalla-Ruiz, E., Gómez Sánchez, M., & Castro, C., *The cumulative vehicle routing problem with time windows: models and algorithm*, Annals of Operations Research, 350(1), 325-353, (2025).

78. Jeong, H. Y., & Song, B. D., *Optimizing Urban Logistics: Vehicle Routing Problem with Underground Transportation*, IEEE Transactions on Intelligent Transportation Systems, 26(5), 6393-6413, (2025).

79. Acar, I., & Altin, I., *Multi-Depot General Colored Traveling Salesman Problem with Time Windows in Home Healthcare System: A Medication Delivery Example*, International Journal of Industrial Engineering: Theory, Applications and Practice, 32(2), 493-513, (2025).

Ranjeeta,
Chitkara University Institute of Engineering and Technology,
India.
E-mail address: `ranjeeta.4100@chitkara.edu.in`

and

Mohit Kumar Kakkar,
Chitkara University Institute of Engineering and Technology,
India.
E-mail address: `mohit.kakkar@chitkara.edu.in`

and

Priyanka,
Chitkara University Institute of Engineering and Technology,
India.
E-mail address: `priyanka.4968@chitkara.edu.in`