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A Vehicle Routing Problem Unsystematic Literature Review

Pietro Piva Vieira[1*]; Davi Duarte[2†]; Gabriel Endres[2‡]; Jean Matos[2§]
Claudia Maia[2¶]; Marcelo de G. Malheiros[2‖]; Rafael Berri[2**]
Giancarlo Lucca[3††]; Leonardo R. Emmendorfer[4‡‡]; Bruno L. Dalmazo[2]

Abstract: This document provides analysis of various methodologies and case studies focused on optimizing routes in logistics and transportation. It examines techniques used to enhance efficiency in waste collection, goods distribution, and delivery services through advanced algorithms and commercial software. The study explores the integration of hybrid optimization algorithms and heuristic approaches to achieve significant cost and time savings. It also reviews advancements in handling uncertainties in dynamic vehicle routing and presents sophisticated algorithms for solving online stochastic vehicle routing problems. The findings underscore the importance of innovative technologies and strategic planning in improving logistical operations and route optimization.

Keywords: Vehicle Routing Problem; Dynamic VRP; Unsystematic Literature Review.

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[*]pietrovieira.aluno@unipampa.edu.br
[†]daviduarte9996@furg.br
[‡]gabriel.endres@furg.br
[§]jeandmalves@furg.br
[¶]claudiarmaia@hotmail.com
[‖]mgm@furg.br
[**]rafaelberri@furg.br
[††]giancarlo.lucca@ucpel.edu.br
[‡‡]leonardo.emmendorfer@ufsm.br
dalmazo@furg.br
[1]Programa de Pos-Graduação em Engenharia de Software, Universidade Federal do Pampa (UNIPAMPA), Alegrete.
[2]Centro de Ciencias Computacionais, Universidade Federal do Rio Grande (FURG), Rio Grande.
[3]Centro de Ciencias Sociais e Tecnológicas. Mestrado em Engenharia Eletrônica e Computação, Universidade Católica de Pelotas, Pelotas.
[4]Programa de Pós-Graduação em Ciência da Computação, Universidade Federal de Santa Maria, Santa Maria.

1 INTRODUCTION

Nowadays, after the advent of the 2020 pandemic, there has been noticeable progress in delivery services, both in food delivery through specific platforms and e-commerce focused on delivering to consumers in the shortest possible time. In this regard, we raise a relevant question: How to deliver items to consumers in the shortest possible time while respecting potential restrictions, given that trucks (in the case of e-commerce) or motorcycles (in the case of app-based delivery) have a maximum weight and volume limit they can carry? Other restrictions are also possible and applied to different problems in this same area.

This problem is not new, with comprehensive reviews already existing on it, as seen in Pillac *et al.*, 2013, academically known as the Vehicle Routing Problem (VRP) and having various variations such as the Capacitated VRP (CVRP) when vehicles have finite capacity and VRP with Time Windows (VRPTW), where the customer must be visited within a specific time window. Both are commonly found in the delivery area since customers often need to receive a delivery within 1 hour, for example. Besides these variations, it is also possible to classify the same problem into some subtypes, considering whether prior knowledge of the points to be visited (problem input) is available and if any parameters may change after the journeys begin.

With the evolution of work in the area, a shift in approaches is evident. Previously, most works addressed a static version of route generation. The dynamic part of the problem has been addressed over time, complicating resolutions and mathematical modeling. As discussed in Pillac *et al.*, 2013, any mode has an objective function. When the problem is static, one can think of an objective like saving on route costs, while with the dynamic notion, we gain a wider range of objectives such as increasing the number of orders per hour or maximizing revenue.

In this work, we will conduct a non-systematic review of past works, focusing mainly on problems related to Dynamic Vehicle Routing Problems (DVRP) and their modeling, how they were approached, and what solutions were used. The main goal is to identify the most common methods for solving each type of problem and how the area has evolved over the years, with a significant increase in related articles relatively recently.

The next sections of this work are organized as follows: Section 2 introduces the VRP and its variations. Next, section 3 discusses different algorithms, heuristics, and metaheuristics used to solve the VRP, elaborating on the most commonly used ones. Then, section 4 presents the results of our research, followed by section 5, where the work is concluded. Finally, we present the acknowledgments and recognition's associated with this research.

2 The variations of the VRP

As seen at Psaraftis, Wen, and Kontovas, 2015, the VRP, as many problems known to Computer Scientists, have many variations that are created based on real-world constraints. When focusing on the it only, we have a few variations that can be tackled and solved:

- Capacitated VRP: When the requester has a demand for goods/products, but the vehicles that are assigned to the task has a limited capacity;
- VRP with Time Windows (VRPTW): A location can only be visited during specified time windows;
- VRP with Pick-Up and Delivery (PDP): In this variation, the objective is to plan routes for a fleet of vehicles that will not only travel a path, but will also take cargo, deliver it and return to some place such as a warehouse or a restaurant to pick up new cargo that will be delivered later.;
- Heterogeneous Fleet VRP (HVRP): A Capacitated VRP, but there are multiple vehicles with different carrying capacities;
- Dial-A-Ride Problem (DARP): A VRP variation, where there are passengers that need to move between different locations, being the starting and finish point known beforehand, being possible to have some restrictions across the route;
- Dial-A-Flight Problem (DAFP): The same as DARP, but for aerial vehicles.

Those variations also have taxonomies that specialize even further the solution that should be created to solve it, by considering the existence of previous knowledge about the locations that should be visited and if there is any parameter (like traffic, weather conditions) that can change after the start of a route.

- Static and Deterministic: All the information needed to solve the problem is known beforehand and it does not change during the execution;
- Static and Stochastic: There is a level of uncertainty about some parameter needed to solve the problem. I.e. a moving service know the start and finish points of a route, but there is no information about the weight and volume of the furniture;
- Dynamic e Deterministic: Some information is known beforehand, but new, constant information can arrive during the execution of a route. I.e. an app driver receive new rides when he/she is executing another one. The ride requests are new, but the start and finish points are known;
- Dynamic e Stochastic: The input is partially known or can change during the execution, but the stochastic data can be explored. I.e. a delivery service receive new orders, but because of the traffic conditions, the travelling time may vary and the customers are notified about possible delays.

3 Algorithms and Heuristics

In the work by Psaraftis, Wen, and Kontovas, 2015 (9), a taxonomy based on 11 criteria was developed using 117 articles. Three of the 11 criteria stand out here: the VRP variation, the objective function, and the method applied in the solution. These are particularly interesting for understanding which methods are generally applied to which types of VRP variations. Regarding the VRP variation, addressed in chapter 2, it was found that 71 out of the 117 articles dealt with the dynamic and deterministic VRP variation. The most popular objective functions for each problem were travel time, route distance, route cost, and customer dissatisfaction, all of which are minimization problems. As for the types of solutions found, we had the following after reading the the mentioned articles:

- **Tabu Search (TS)**: Previously used for the static version of the problem, it was adapted for DVRPs. It is a metaheuristic search method that applies the local search method.
- **Neighborhood Search (NS)**: Consists of search heuristics that explore the neighborhood of a current solution to find better solutions.
- **Insertion Methods**: Heuristics based on efficiently inserting new deliveries into existing routes, used in this type of problem to determine which deliveries will be accepted and which will be rejected.
- **Nearest Neighbor (NN)**: The static version of the dynamic nearest neighbor policy (DNN) used to operate fleets of vehicles serving customers in Euclidean areas.
- **Column Generation (CG)**: Based on real-time column generation to minimize the total route distance, solving problems with strict time windows by operating an optimization that reduces larger problems into subproblems (single trips).
- **Genetic Algorithms (GA)**: Genetic algorithms that incorporate real-time information, improving the quality of solutions with variable travel times. These are based on natural evolution, using operators such as selection, crossover, and/or mutation.
- **Ant Colony Optimization (ACO)**: Optimization algorithms based on ant behavior, using artificial pheromones to guide the search for solutions. They are also applied to find the shortest path in graphs.
- **Particle Swarm Optimization (PSO)**: An optimization algorithm inspired by the belief that groups of animals can benefit from the individual experience of each member, used to find the minimum or maximum of a function.
- **Waiting-Relocation Strategies**: A strategy based on the reasoning that, at certain times, the best decision may be to wait before assigning to the customer. This may even include adding fictitious customers (past customers) who have not yet made any requests but may end up doing so.

- **Markov Decision Processes (MDP)**: Mathematical modeling of a decision process for situations where outcomes are partly random and partly under the control of a decision-maker, who, in this context, may be referred to as the driver.
- **Dynamic Programming (DP)**: A method used to solve complex problems by breaking them down into simpler sub-problems. The approach of DP involves caching the results of each sub-problem, a technique that optimizes the algorithm execution by avoiding redundant computations, leading to more efficient solutions.
- **Queueing-Polling Strategies**: As mentioned in Psaraftis, Wen, and Kontovas, 2015, these are queuing and polling systems with multiple queues accessed by a single server in a cyclic order. They can be used to manage a fleet of vehicles serving customers in different locations, aiming to optimize the service order to minimize wait time.

In the article by Ulmer *et al.*, 2020 (12), a variation of VRP known as Stochastic Dynamic Vehicle Routing Problems (SDVRP) is addressed, where customers are geographically dispersed and visited by one or more vehicles. It is considered a dynamic problem because information continues to arrive stochastically throughout the working hours, necessitating new decisions with the newly revealed information. They proposed a mathematical modeling for such problems due to the lack of standardized frameworks in this area, using MDP as a base and extending it to the proposed framework: route-based MDP, composed of decision epochs, states, rewards, transitions, and objectives, but redefines the space of viable actions to include route plans. In the article, this new framework is compared with 4 existing ones: Reoptimization (RO), Policy Function Approximation (PFA), Lookahead Algorithm (LA), and Value Function Approximation (VFA), concluding that the proposed model is more robust compared to the others evaluated.

In the work by Fournier, 2022 (1, 2, 3, 4, 5, 6), the pandemic context is taken into consideration along with the specific difficulties of generating routes for heavy vehicles. Some particular difficulties include the existence of certain streets where heavy vehicles cannot pass and also regarding the workers, as the generated routes must have specific times for the drivers to rest and cannot exceed the number of hours established by law. Some companies were studied for route calculation and optimization such as: Here Technologies, Tomtom, Sygic, Widescope, Workwave, OptimoRoute, Google OR-tools. Another one for driver management analysis: Trackit, to measure the legal driving time of drivers controlled through tachographs, a device installed in vehicles that records usage time, distance, and speed, essentially a telemetry device. To generate the software, the Google OR-Tools tool was used, a library that contains several specific algorithms for optimization problems. The relevant algorithms in this context implemented in the tool are as follows: Path Cheapest Arc, Path Most Constrained Arc, Savings, Sweep, Christofides, Best Insertion, Parallel Cheapest Insertion. In summary, the work predominantly used Geocode, CalculateRoute, and CalculateMatrix services from HERE Technologies and

Google OR-Tools.

With the aim of improving resource estimation, such as fuel, time, and carbon emissions, also reducing fuel use and carbon emissions through supply chain route optimization and making the supply chain more efficient, the work by Chowlur Revanna *et al.*, 2023 (7) proposed 3 steps to achieve these goals:

- Use the Geopointe tool to create, plan, and execute all necessary arrangements for the trip
- Location information from Salesforce products (CRM platform – to manage customers and their connections), Google, or similar will be used to create the routes
- Get travel directions through Google, managing up to 100 stops per route, generating optimized routes.

A comparison with other tools was carried out, and the combination with the best results was Salesforce used together with Geopointe, applying Google Maps for spatial data analysis, and finally applying the Ant Colony Optimization (ACO) algorithm, achieving a robust solution to optimize routes and processes.

In table 1, the algorithms used in the analyzed works and software for route optimization are presented, cross-referenced with which works they appeared in. With, respectively, 4 and 5 appearances in the 15 articles, we had Genetic Algorithm (GA) and the graph optimization algorithm Ant Colony Optimization (ACO), which were used together 3 times, indicating they are a good pair for dealing with VRP and its derivatives. It is worth noting that the Dijkstra algorithm and its variations were found cited only 2 times in the examined articles, probably because there are more robust solutions for route optimization in graphs. Three articles were found using the Google Maps tool, with the main intention of using the mapping tool to later apply optimization algorithms for route generation. A well-observed point in the studied works was the concern both financially, aiming to reduce costs and increase profits for companies operating with vehicle fleets, and environmentally, with a greater focus on reducing carbon emissions. It is worth mentioning that even if the goal is only one of these, we will achieve both with good solutions in the area of route optimization.

4 Results

The current section provides the outcome of our research, pointing out interesting details and results from the studied papers.

We selected and read 15 papers related to the Dynamic VRP, and then pointed out what algorithm, heuristic/metaheuristic or commercial software was used by the solution. The results of this mapping is displayed on the table 1.

Then, the papers were splitted equally between the authors of this paper. Each author provided a short description of each paper, highlighting the advances, techniques and results of each paper.

Starting by Apaydin, 2007 (15), the optimization of solid waste collection and transportation in Trabzon, Turkey is examined. The study used video recording, GPS data, and various factors such as truck type and capacity, population, and solid waste production. Route optimization was achieved using the Route View Pro software, incorporating Geographic Information System (GIS) elements like numeric pathways, demographic distribution, container distribution, and waste production data. The optimized routes showed improvements of 4-59% in distance and 14-65% in time compared to current routes, and highlighted a 24% reduction in the total cost of the stationary container collection system.

Li, 2015 (7) discusses using an ant colony optimization algorithm to improve efficiency in the logistics sector. The hybrid ant colony algorithm incorporates quantum computing to encode and update pheromones, demonstrating strong global search capability and convergence speed. The algorithm involves solution construction by ants, pheromone updates based on optimal solutions, and final solution generation, effectively solving distribution route problems and outperforming traditional algorithms.

Vasconcelos, Pereira, and Real, 2023 (6) addresses the need for an accessible platform to optimize delivery visit sequences for small entrepreneurs. Using the Traveling Salesman Problem and 2-opt heuristic, the app, developed with React Native and JavaScript, quickly finds efficient routes. Field research showed existing high-cost solutions, prompting the creation of a simple route optimizer. The app calculates routes using Google API data and 2-opt heuristic, optimizing delivery efficiency.

Ninja, Marlin, and Dirk, 2022 (12) reviews advances in solving stochastic dynamic vehicle routing problems (SDVR), crucial for logistics and mobility services. The review covers uncertainty modeling, solution approaches, and relevant studies, highlighting the application of prescriptive analytics to improve vehicle routing efficiency in uncertain environments.

Saint-Guillain, 2019 (11) focuses on online stochastic vehicle routing problems (VRPs) and presents two algorithms: branch-and-price and branch-and-price-and-cut, both based on column generation techniques. These algorithms are designed to solve VRPs with stochastic demands, providing exact solutions by generating additional columns for linear programming relaxation and adding valid cuts for optimization.

Gmira *et al.*, 2021 (5) focus on real-time management of routing plans, using the Tabu Search heuristic to adapt routes according to variations in travel times, like traffic jams, resulting in increased logistical efficiency on adapting routing in response to unforeseen events.

Ritzinger, Puchinger, and Hartl, 2016 (9) makes a comprehensive review, highlighting the integration of dynamic information to enhance the accuracy of routing solutions. The outcome of this survey points out that there are multiple algorithms used to solve the VRP, including methods that use real-time optimization based on dynamic data input.

Lesch *et al.*, 2022 (8) presents a case study that utilizes linear programming and genetic algorithms to optimize delivery routes. The implementation of said techniques reduced operational costs and delivery times and highlighted the efficiency in combining deterministic and evolutionary methods to tackle the complexity of the VRP.

Zhang *et al.*, 2023 (13) shows a multi-stage model based on linear approximations is proposed to solve dynamic vehicle routing problems with stochastic requests, demonstrating effectiveness in large real-world instances. It utilizes linear approximations based on the classic Knapsack problem, showing the efficiency of said method to plan offline routes with high quality and good online scheduling decisions

Finally, Zhang and Woensel, 2023 (14) synthesize advances and identifies gaps in the research on dynamic vehicle routing with random requests, suggesting the integration of advanced machine learning techniques to improve the adaptability and efficiency of routing systems. It highlight's the necessity of algorithms that can adapt to the uncertainties and dynamism of the real world, suggesting that Machine Learning should be integrated to real time optimization to provide better efficiency and throughput.

5 Conclusion

The Vehicle Routing Problem (VRP) remains a fundamental challenge in logistics and transportation, driving continuous research and innovation in optimization techniques. This systematic literature review has highlighted the advancements in algorithms, methodologies, and heuristics/meta-heuristics, revealing a diverse range of approaches tailored to solving complex routing problems. From local search methods and meta-heuristics like Tabu Search and Ant Colony Optimization to the integration of Artificial Intelligence (AI), the field has evolved to address the increasing demands of modern fleet operations.

Scalability is a critical aspect of VRP optimization. Recent strategies enabled the handling of large datasets and dynamic conditions more efficiently.

In summary, the state-of-the-art in VRP optimization is characterized by a blend of advanced algorithms and cutting-edge technologies. The continued exploration and application of these innovations are essential for addressing the complexities of modern transportation logistics, ultimately leading to more sustainable and effective fleet operations.

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7 Appendices

Table 1: Algorithm/Commercial Software used on each article

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Path Cheapest Arc										✓					
Path most constrained Arc										✓					
Savings										✓					
Sweep										✓					
Christofides										✓					
Best Insertion										✓					
Parallel Cheapest Insertion										✓					
Algoritmo Genético		✓			✓	✓			✓						
Ant Colony Optimization					✓	✓	✓		✓				✓		
Linear Models Knapsack e Variações											✓				
Dijkstra e Variações			✓											✓	
Algoritmo 2-opt			✓				✓							✓	
Shortest Path Model	✓														
Neuro-Dynamic Programming						✓									
Branch-and-price Algorithm															✓
Tabu Search Algorithm						✓									✓
Variable Neighborhood search algorithm						✓									✓
Non-parametric value function approximation															✓
multiple scenario approach algorithm		✓										✓			
post-decision rollout algorithm												✓			
route-based markov decision processes (MDP)						✓		✓							
Gravitational Search Algorithm							✓								
Multiple Sequence Alignment Algorithm							✓								
Multi-Start Algorithm				✓											
Particle Swarm Optimization (PCO)						✓									
Approximate Dynamic Programming (ADP)		✓					✓								
Linear Programming		✓													
Dynamic Sample Scenario Hedge Heuristic (DSHH)		✓													
Geopointe										✓			✓		
Workewave										✓					
OptimoRoute										✓					
Google Maps							✓						✓	✓	
Salesforce Map													✓		
Route View Pro	✓														
GIS	✓														

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