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Challenges and Opportunities for Applying Meta-Heuristic Methods in Vehicle Routing Problems: A Review †

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Abstract: The Vehicle Routing Problem (VRP) is related to determining the route of several vehicles to distribute goods to customers efficiently and minimize transportation costs or optimize other objective functions. VRP variations will continue to emerge as manufacturing industry production distribution problems become increasingly complex. Meta-heuristic methods have emerged as a powerful solution to overcome the complexity of VRP. This article provides a comprehensive review of the use of meta-heuristic methods in solving VRP and the challenges faced. A review of popular meta-heuristic methods is presented, including Simulated Annealing, Genetic Algorithm, Particle Swarm Optimization, and Ant Colony Optimization. The advantages of each method in solving the VRP and its role in solving complex distribution problems are discussed in detail. Challenges that may be encountered in using meta-heuristics for VRPs are analyzed, along with strategies to overcome these challenges. This article also recommends further research that includes adaptation to more complex VRP variants, incorporation of meta-heuristic methods, parameter optimization, and practical implementation in real-world scenarios. Overall, this review explains the important role of meta-heuristic methods as intelligent solutions to increasingly complex distribution and logistics challenges.

Keywords: vehicle routing problem; optimization; metaheuristic methods; simulated annealing; genetic algorithm; particle swarm optimization; ant colony optimization

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1. Introduction

1.1. Background and Significance

The Vehicle Routing Problem (VRP) is an optimization problem that involves setting the travel route for a group of vehicles, which must visit several customer points, by minimizing the total distance traveled or other operational costs. It has been shown that solving vehicle routing problems has a major contribution to efficiency and cost reduction in various sectors, including distribution [1]. VRP optimization research is an important study area because goods delivery problems are becoming increasingly complex and require appropriate planning so that costs can be minimized and efficiency can be increased [2]. In addition, VRP solutions help companies optimize goods delivery, and customers can receive their products on time, thereby increasing customer satisfaction [3]. Efficient VRP solutions can help reduce greenhouse gas emissions and air pollution, as reducing travel distance and travel time automatically reduces fuel consumption. This effort also gave rise to the term, Green Vehicle Routing Problem [4].

Research related to the VRP can help create better, more efficient, and sustainable solutions in transportation and logistics management. There are many methods used to complete VRP solutions, such as (a) the exact method, which finds the optimal solution by calculating every possible route combination, and some mechanisms are applied to reduce unnecessary checking of solution combinations [5]; (b) the heuristic method, which uses simple rules to generate adequate solutions quickly [6]; (c) the meta-heuristic method, which combines several heuristic techniques to produce better and faster solutions; and (d) the hybrid method, which combines several heuristic and meta-heuristic techniques to produce better and faster solutions.

Exact methods or complete enumeration algorithms can be applied to obtain optimal solutions for small-scale VRP problems. However, for large problems with many visiting points, the complexity of VRPs will increase exponentially. This underlies why the meta-heuristic approach is the right choice. In recent years, meta-heuristic methods have emerged as a powerful approach to handle complex optimization problems such as VRPs [7]. However, due to the complexity of the existing VRP variants, its implementation still faces several challenges that must be taken seriously. The novelty of this review article is that it highlights and analyzes the unique challenges faced when applying meta-heuristics to VRPs, such as premature convergence, parameter dependency, and scalability on large VRP instances. Furthermore, this paper provides practical guidance needed to overcome these challenges by using several strategies to exploit the advantages of meta-heuristic methods in achieving better and more efficient solutions to VRPs.

1.2. Aim and Scope of the Review

The primary objective of this review is to explore how heuristic methods have been utilized in solving variations of the Vehicle Routing Problem (VRP). The scope of this review will discuss opportunities and challenges for further development regarding the application of meta-heuristics to VRPs. With this review, we can identify promising research avenues to overcome existing challenges and exploit the potential that has not been fully explored in previous studies.

1.3. Paper Structure

We designed the structure of this paper in a systematic way to help readers fully understand our exploration of the use of meta-heuristic methods in solving VRPs. In the "Introduction" section, we explain the importance of solving VRPs and why meta-heuristic methods are the right choice for VRPs. The basic concepts of the VRP, including the level of complexity in solving it, are presented in the "Vehicle Routing Problem: Basic Concepts" section. Next, in the "Meta-Heuristic Method" section, we discuss the concept of meta-heuristic methods, which are composed using several heuristic strategies. Various advantages of meta-heuristic methods are discussed and related to the complexity of the VRP. The section "Popular Meta-Heuristic Methods in VRP" presents several meta-heuristic methods that are often chosen by researchers to solve VRPs. For each method, the working principles, advantages, and limitations in solving the VRP are explained. The main part of this review is devoted to "Opportunities and Challenges for Further Development". This section explores potential avenues for extending meta-heuristic approaches for VRPs. In "Conclusion", the current review's findings are highlighted. This section also outlines the potential effects and research opportunities designed to address the problems with meta-heuristic techniques in tackling the VRP.

2. Vehicle Routing Problem: Basic Concepts

To choose the best meta-heuristic method for solving complex VRP problems, it is necessary to first understand the meaning and various forms of the VRP.

2.1. Definition and Variants of VRP

The Vehicle Routing Problem (VRP) is a combinatorial optimization problem that aims to determine the optimal route for a number of vehicles to serve requests from several customers. Each customer has a request for several goods or services that must be fulfilled within a certain time frame. The vehicles depart from the same point (usually a factory, depot, or warehouse) to the customer's location. Each vehicle has a certain capacity to transport goods. The goal of finding a VRP solution is to obtain the minimum total distance traveled by all the vehicles, minimize transportation costs, and maximize the number of customers served [8]. As the manufacturing industry has developed with an interest in distributing its production results, various variations of the VRP have emerged. VRP variants have been identified based on different problem complexity, constraints, and objectives. Some common variants include:

(a) Vehicle Routing Problem with Time Windows (VRPTW): Each customer has a time window when they can receive service [9,10];
(b) Capacitated Vehicle Routing Problem (CVRP): Each vehicle has a limited capacity to transport goods [11];
(c) VRP with Pickup and Delivery (VRPPD): Vehicles not only deliver goods but also pick up goods from other customers during the journey [12,13];
(d) Time-Dependent VRP (TDVRP): Considers time as an important factor in determining the optimal route for delivery [1];
(e) Multiple Depot VRP (MDVRP): Several depots or distribution centers are used as the starting and ending points of delivery routes [14].

Variations in VRPs will continue to emerge as manufacturing industry production distribution problems become increasingly complex, and competition between companies increases to produce the best products at the lowest costs. Several researchers have also proposed new names and variants that are more specific, according to the problem being solved. An example is the Vehicle Routing Problem with Divisible Deliveries and Pickups (VRPDDP), which allows customers to be served by several visits on the same or different routes. Since each point can involve both delivery and pickup, the number of possible route combinations increases significantly, making it difficult to find the optimal solution [15].

Another example is the Collaborative Multicenter Vehicle Routing Problem with Time Windows and Defaulting Members Withdrawal (CMVRPTWDMW), which involves collaboration between several distribution centers, time restrictions for customer visits, and the possibility of members (distribution centers) leaving the collaboration [16]. The main challenge in completing this VRP variant is balancing route efficiency, meeting time constraints, and change management when there is member withdrawal. Understanding these VRP variants is very important in the context of using meta-heuristic methods because each variant has unique challenges and characteristics that affect the performance of the algorithm used.

2.2. VRP Complexity

Vehicle Routing Problems (VRPs) are optimization problems that are recognized as having a high level of complexity. This complexity arises from a combination of factors such as the number of customers, vehicles, and restrictions in place. Although the VRP in its basic form is an NP-hard problem, more complex variations and deeper constraints may lead to a class of problems that are even more difficult to solve efficiently. The complexity of VRPs can be viewed from two main perspectives: computational time complexity and combinatorial complexity [16]. In terms of computational time complexity, finding the optimal solution for the VRP with exact methods can take a very long time when the problem gets bigger and involves more variables. Combinatorial complexity is related to the number of possible solutions that must be explored in finding the optimal route for each vehicle. For example, in the case of a VRP involving 50 customers that must be served, there are at least 50! or 3.04×1064 possible solutions. For VRPs with a significant number of subscribers, the search space that must be explored may exceed the practical computing capacity. By exploring VRP variants and possible limitations in real scenarios, we will be able to identify how this approach can provide efficient and accurate solutions even when faced with very complex optimization problems.

3. Meta-Heuristic Method

In this chapter, we will review the basic concepts and principles of meta-heuristic methods as a powerful approach to solving complex optimization problems such as VRPs.

3.1. Concepts and Basic Principles of Meta-Heuristic Methods

The meta-heuristic method consists of several heuristic methods. The heuristic method is a search method based on empirical rules to obtain a better solution than the solution that has been achieved previously. By using an initial solution that may be generated randomly, the heuristic method gradually tries to get a better solution in subsequent iterations. Although it does not always produce an optimum solution, if it is designed well, it will produce a solution that is close to optimum in a relatively short time.

The meta-heuristic methods are focused on developing search algorithms that can effectively explore a range of potential solutions without being limited to a single path and strict boundaries. In the context of organizing several heuristic algorithms, the meta-heuristic algorithm acts as a "manager" of several heuristic algorithms to organize the search for a solution to a problem systematically. With this approach, meta-heuristic algorithms can design global strategies that control how the heuristic algorithm works, combine the results of different heuristic algorithms, or regulate how the heuristic algorithm is executed based on a certain policy. With this mechanism, meta-heuristic methods are, essentially, "algorithms for organizing algorithms". An example is the Variable Neighborhood Search (VNS) method, which manages a local search (LS) technique [17]. VNS systematically iterates LS to find solutions from different starting points and covers a wider search area. Another example is the Genetic Algorithm (GA), which organizes several genetic operators such as crossover, mutation, and selection [18].

3.2. Advantages of Meta-Heuristic Methods in Combinatorial Problems

Several studies have proven that the meta-heuristic method is an effective method in solving difficult and complex combinatorial problems. The main advantage of meta-heuristic methods lies in their flexibility and adaptability in handling large search spaces, which are often difficult to access with traditional exact or heuristic methods [19]. In complex combinatorial problems such as VRPs, the ability of meta-heuristic methods to handle this complexity is invaluable.

Optimization techniques aim to produce optimal solutions that require a balance between exploration and exploitation capabilities. Exploration is the ability of an algorithm to explore areas that have not been visited, while exploitation is the ability of an algorithm to use areas that have been explored and find possible better solutions [6]. Traditional heuristic approaches may produce suboptimal solutions because the search process is stuck at a local optimum. This is especially the case if the location of the first random solution is far from the best solution. Meta-heuristic methods, on the other hand, are capable of extensive exploration to find better solutions during their iterative process. This method can jump the local optimum and obtain better results overall [20]. In addition, meta-heuristics also have flexibility in combining various types of search strategies. They can combine the best elements of various heuristic approaches to form more robust and adaptive algorithms [6]. For VRPs, where variations and constraints require multiple approaches, this capability provides additional benefits in achieving better and more appropriate solutions to the situation at hand.

4. Popular Meta-Heuristic Methods in VRPs

This chapter discusses several meta-heuristic approaches with proven effectiveness in solving VRPs and related variations. We conducted a simple search on the Scopus database using the keywords 'vehicle AND routing AND problem AND genetic AND algorithm' to find how many published documents contain these keywords from 2000 to 31 November 2023. The complete results including other meta-heuristic methods are presented in Table 1.

Table 1. Search results.

No	Method	Number Documents
1	Genetic Algorithm	2614
2	Ant Colony Optimization	1192
3	Simulated Annealing	833
4	Variable Neighborhood Search	782
5	Particle Swarm Optimization	703
6	Evolutionary Strategy	219
7	Tabu Search	76
8	Firefly Algorithm	75

4.1. Genetic Algorithm (GA)

The GA is a popular meta-heuristic method and is often used to solve various complex optimization problems, including VRPs. GA is inspired by natural evolutionary processes. In this natural evolutionary process, if higher quality individuals are given the opportunity to reproduce more and have a greater chance of being retained in the next generation, then the next generation will produce better individuals. This mechanism is adopted by GA by using individuals as solution representations. Genetic operators such as crossover, mutation, and selection are used to explore the search space. The advantage of GA lies in its ability to perform searches in a wide and unstructured search space. This capability makes GA a suitable approach for solving varied VRP problems [2]. GA can also carry out a parallel search process, where GA is run on several computers simultaneously. This makes the solution search process faster than other meta-heuristic methods [21]. By using various genetic operators specifically designed for specific VRP variants, the Genetic Algorithm can find better solutions through the evolutionary process [2].

4.2. Ant Colony Optimization (ACO)

ACO is an algorithm inspired by the movements of groups of ants. When ants search for food trails, they leave pheromone trails on the surface of the soil. This trail becomes stronger when many ants have passed through it. Therefore, other ants are expected to follow the trail of higher-intensity pheromones so they can get food more quickly. The nodes on the graph represent depots and customers in the VRP. The weight of each node is the distance or cost to reach that node. Each ant starts its journey at the depot. The ant determines which direction to turn with a probability that depends on the strength of the pheromone on that path. After that, the ant continues to its destination, leaving behind a trail of pheromones. This pheromone indicates that the path is in a good direction. This allows ACOs to work effectively in VRPs with complex network structures and many customers. ACO has been used to solve CVRPs [4], VRPTWs [7,22], and VRPPDs [23].

4.3. Simulated Annealing (SA)

SA is a popular meta-heuristic method for solving complex optimization problems including VRPs. SA can be easily modified to suit different VRP variants. The metal cooling process inspired SA. In the search space, exploration and exploitation are controlled through a process of gradual temperature reduction. In the early stages of an iteration, the algorithm has a high probability of accepting a worse solution. This mechanism allows SA to escape from local minima. The probability value over time decreases so that the algorithm leans towards a better solution. As a relatively easy-to-modify method, SA has also been used in several studies. For example, one study aimed to solve the problem of vehicle routing with limited time windows, which involved many warehouses, many products, and many customers [10]. SA was also used to complete a VRPTW, and the results were compared with agent-based simulations [24].

4.4. Variable Neighborhood Search (VNS)

VNS works with an iterative approach consisting of two main phases: search within a given environment and consideration of movement to a different environment. With its iterative approach, VNS starts with an initial solution and performs a search in an "environment" that can be permutations, combinations, or other variations of parameters, depending on the nature of the problem. If the solution in the current environment does not provide significant improvement, the algorithm considers moving to a different environment or changing the rules or search strategy. The search and displacement considerations are repeated iteratively until a solution that meets the convergence criteria is reached. VNS can be easily adapted to meet the needs of varying VRP problems. By setting up various neighborhood structures, VNS can perform well in dealing with variations in the number of customers, vehicle capacity, or changing geographic conditions. VNS has been applied for the Pollution Location Inventory Routing Problem (PLIRP) [17].

4.5. Particle Swarm Optimization (PSO)

PSO is a meta-heuristic method that is also often used in solving VRPs. PSO is inspired by group behavior in nature, such as the movement of groups of birds or fish. In PSO, members of a collection of birds or fish are called particles, which represent solutions to problems. Each particle moves stochastically through the search space to find a better solution based on information from personal experience and the best particle in the group. PSO has the advantage of solving problems that do not have strict mathematical structures or constraints, making it suitable for handling more complex and dynamic VRP variations. By using several swarm collections in different groups to explore the solution search area simultaneously, PSO can be scaled to more complex problems [25]. Previous research provides examples of the application of PSO in a VRPTW [9] and a CVRP [11].

5. Opportunities and Challenges for Further Development

Although meta-heuristic methods have proven effective in solving complex optimization problems, their application to VRPs faces several challenges that require special attention. Understanding these challenges will help us explore the potential and limitations of this approach in solving various VRP variants. In this chapter, the opportunities and challenges that exist for further development in the use of meta-heuristic methods in solving VRPs will be explored. Through this exploration of opportunities and challenges, we will illustrate directions that can be taken in future development and research in solving increasingly complex, real-world VRPs.

5.1. Dependency on Parameters

One of the main challenges in applying meta-heuristic methods to the VRP is the strong dependence on algorithm parameters. Parameters such as initial temperature in SA, population size, crossover rate, and mutation rate in GA, or step size in PSO, can have a significant impact on algorithm performance and convergence. However, finding optimal parameter values is not a simple task.

Determining the appropriate parameter values also depends greatly on the characteristics of the VRP problem being addressed. If parameters are not well-tuned, meta-heuristic algorithms may have difficulty navigating the complex search space and considering a wide range of possible valid solutions [26]. Careful research and experimentation are required to determine the most suitable parameter values for each VRP variant and the type of meta-heuristic used. Approaches such as the use of trial-and-error and automatic parameter tuning have been proposed to overcome these challenges, with the aim of generating optimal parameter combinations to optimize algorithm performance.

5.2. Algorithm Efficiency

On larger problem scales, meta-heuristic algorithms can face significant computational time challenges. The process of searching for candidate solutions involving complex and stochastic operations can take quite a long time to produce a good solution. Therefore, improving algorithm efficiency is a major concern, especially in environments that require fast solutions or where fast optimal solutions are required. Efforts to improve algorithm efficiency involve a variety of strategies. Computational optimization and redundancy reduction in algorithm steps can result in shorter computing times. Selection of efficient solution representations, such as the use of compact genetic codes in Genetic Algorithms, can reduce processing time.

5.3. Possibility of Premature Convergence

Premature convergence occurs when the algorithm stops searching earlier than it should, causing the solution it found to be non-optimal or even suboptimal. The general thing that occurs in population-based methods such as GA and PSO is that the existing solution collections have high similarities, so it is not possible to form alternative solutions that can jump the local optimum. The risk of premature convergence may arise from several factors, including inappropriate selection of search operators or less balanced handling of diversification and intensification. Less effective search operators can cause the algorithm to get stuck in a local solution that cannot be improved further. On the other hand, a lack of diversification, that is, a sufficiently broad exploration of the search space, can cause the algorithm to focus too early on non-optimal solution areas.

To overcome the risk of premature convergence, several strategies can be implemented. The use of a wider range of search operators, as well as the incorporation of various heuristic or stochastic techniques, can help avoid getting stuck in local solutions. The use of adaptive temperature scheduling in Simulated Annealing, or balanced handling of intensification and diversification in algorithms such as the Genetic Algorithm, can help maintain a balance between exploration and exploitation.

5.4. Scalability in Large VRP Instances

Scalability is a significant challenge in applying meta-heuristic methods to VRP problems on larger scales and increasingly complex constraints [22]. As the number of customers, vehicles, or constraints increases, the efficiency and reliability of the algorithm becomes critical to producing quality solutions in a reasonable timeframe. Scalability can be defined as the ability of an algorithm to maintain good performance as the size and complexity of the problem increases. Efficient and adaptive meta-heuristic methods are needed to maintain the problem-solving capabilities of VRP on a larger scale.

Strategies related to scalability include the use of parallelization techniques to take advantage of greater computational capabilities; for example, applying parallel Genetic Algorithms to large CVRPs produces better solutions and much lower computing times [27]. Another strategy is to modify the meta-heuristic algorithm on specific VRP variants to reduce computational complexity. For example, in determining waste collection routes, the adaptive particle swarm optimization method is used, which is equipped with several special strategies for the solution search process [28]. The use of intelligent solution initialization methods and efficient representation can also help reduce processing time and enable exploration of the search space on a larger scale. For example, greedy algorithms and random rules are used to generate the initial population in a Genetic Algorithm to solve VRPPDs [29].

5.5. Meta-Heuristic Hybridization

One effort that is often made in developing solution methods for VRPs is the combination or integration of several meta-heuristic methods. Different methods can complement each other, thereby creating a more robust and adaptive approach. For example, a strong SA in initial exploration is used to generate initial solutions for TS. The next process is carried out by TS, which is good at search intensification [30]. In another study, the best solution produced by GA in an iteration is improved by SA. This mechanism is used to strengthen the exploitation of the local search area [31].

Hybridization of meta-heuristics can not only improve the performance of algorithms in solving VRPs but also enable a more structured approach to solving challenges on more complex VRP variants. Through structured experimentation and analysis, combining meta-heuristics offers the potential to provide more optimal and efficient solutions in solving a variety of VRP problems.

5.6. Adaptation to More Complex VRP Variants

In some situations, VRP can involve more than just determining the optimal route. Variants such as VRPs with time windows, capacity, availability, or even a combination of several of these factors, add more complex constraints and obstacles to finding quality solutions [32]. Specific adaptation and modification of meta-heuristic methods to address more complex VRP variants require innovations in modeling, search operator design, and parameter tuning. For example, PSO is enhanced with a two-stage search mechanism. This mechanism is needed to regulate when the VNS method is involved in finding solutions during PSO iterations [13]. In large cases, determining vehicle allocation for each consumer and simultaneously determining the route for each vehicle requires quite a lot of computing time. In the study on VRPTW completion, the K-Means clustering method is used to group consumers first, and then look for routes for vehicles that serve consumers in one group [33].

5.7. Meta-Heuristic Parameter Optimization

Parameters such as initial temperature in SA, population size in GA, or speed factor in PSO have a significant impact on the performance and convergence of the algorithm. Therefore, proper parameter settings are essential to achieve a good and efficient solution. For example, searching for a CVRP solution using a combined Artificial Bee Colony (ABC) and SA method requires preliminary trials to determine the best parameters for both methods. For ABC, trials are needed to determine the best population size parameter values. In SA it is necessary to determine the value of the temperature reduction factor and variables to regulate the probability of accepting a worse solution [24]. When applying GA, it is necessary to determine the values of population size, number of generations, crossover rate, and mutation rate [2].

6. Conclusions

This review presents broad implications of the application of meta-heuristic methods in solving various variants of VRP. The first implication is that the meta-heuristic method has proven itself as a powerful approach to overcoming VRPs, especially when faced with problems with large-scale, route complexity, and various complex constraints. These implications have a positive impact on the distribution and logistics industry, with the potential to optimize operations, reduce costs, and increase efficiency. By utilizing meta-heuristic methods to plan more efficient routes, companies can make faster and more accurate deliveries to their customers. This has a direct impact on increasing customer satisfaction and allows the company to maintain and increase market share. The potential impact also extends to environmental and sustainability aspects. By planning more efficient routes, fuel use and greenhouse gas emissions can be reduced. Apart from its practical impact, the use of meta-heuristic methods in VRPs also opens up opportunities for further research. Research in this area could focus on developing more adaptive and intelligent algorithms. The potential to incorporate further meta-heuristic methods also presents new opportunities to design more effective approaches.

Several studies have indicated that meta-heuristic methods can effectively be used in VRPs, yet there are many areas to research further. One opportunity involves developing algorithms that are more adaptable to changes in the operational environment. This is also shown in various studies that are conducted on specific models of VRP that are present in different real-world scenarios. Further research could also focus on predicting changes in customer demand, traffic, and vehicle conditions, as well as other factors that may impact route planning. Researching the hybridization of meta-heuristic methods may also be challenging. Moreover, more research could be carried out to develop more efficient and accurate meta-heuristic methods of dealing with complex VRP variants. This enables the development of search operators that address the characteristics of each variant, which can lead to more optimal and targeted solutions in diverse business environments. Lastly, research can also involve meta-heuristic method application and their adoption in various industries. Some research may entail developing software or tools that will facilitate companies' adoption and adaptation of meta-heuristic methods in routine operations. This call for continued research encourages the scientific and industrial communities to collaborate to address increasingly complex challenges in distribution and logistics optimization.

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