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Systematic Review

A Systematic Literature Review of Vehicle Routing Problems with Time Windows

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Abstract: Vehicle routing problems with time windows (VRPTW) have gained a lot of attention due to their important role in real-life logistics and transport. As a result of the complexity of real-life situations, most problems are multi-constrained and multi-objective, which increases their difficulty. The aim of this paper is to contribute to the effective solution of VRPTW-related problems. Therefore, research questions and objectives are set in accordance with PRISMA guidelines, and data extraction and analysis of the relevant literature within the last five years (2018–2022) are compared to answer the set research questions. The results show that approximately 86% of the algorithms involved in the literature are approximate methods, with more meta-heuristics than heuristics, and nearly 40% of the literature uses hybrid methods combining two or more algorithms.

Keywords: vehicle routing; vehicle routing problems (VRP); vehicle routing problems with time windows (VRPTW); time windows

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1. Introduction

Vehicle routing problems with time windows (VRPTW) is a widely recognized problem in the field of logistics, involving the optimization of delivery routes for a fleet of vehicles, while considering specific time windows for each delivery. VRPTW is a notable variant within the broader context of vehicle routing problems. It was first proposed by Solomon [1] in 1987. Nowadays, as logistics plays a vital role in supply chain management and transportation, VRPTW has gained significant attention from the research community due to its numerous real-world applications. For example, waste collection [2,3], home healthcare [4,5], perishable goods delivery [6], municipal solid waste collection [7], home delivery [8], bus route optimization [9], ride-sharing services [10], customized bus service [11], among others [12–24].

However, finding an optimal solution for VRPTW is a non-deterministic polynomial-hard problem [1], and the complexity of the problem increases significantly with the size of the input data. Therefore, researchers use less exact algorithms to obtain optimal solutions, but more approximation algorithms to find acceptable approximate solutions. Numerous approximation algorithms have been proposed to address this challenge, such as single algorithms [2–17], hybrid algorithms [18–30], and machine-learning methods [31], but there is still a need for more effective and efficient solutions to optimize vehicle routes.

In recent years, VRPTW has become an active area of research, and several studies have focused on developing new algorithms and techniques to improve the efficiency and effectiveness of vehicle routing. However, despite significant progress, there are still several challenges that need to be addressed, including the incorporation of multiple constraints [2–5,13–16,32–45], multiple objects [2,4,5,16,45–48], the use of realistic datasets [4,28,49,50], and the adaptation of solutions to real-world scenarios [8,9,20,25,28,38,51–53].

Another important challenge in the context of VRPTW is the evaluation and comparison of existing algorithms. Several metrics have been proposed to evaluate the performance of these algorithms, such as solution quality, computational time, and scalability. However, the selection of appropriate metrics and the comparison of different algorithms is a complex task that requires a thorough analysis of the strengths and weaknesses of each method.

Moreover, the development of practical applications of VRPTW requires a multidisciplinary approach that takes into account not only technical optimization aspects, but also real-world constraints, such as environmental factors [29,35,54,55], social responsibility [36,51], and economic sustainability [29,34,39,43,55–58]. Therefore, research in this area must focus on the integration of optimization algorithms with other disciplines to ensure that the solutions are practical and relevant.

In this context, a systematic literature review of VRPTW research can provide a comprehensive analysis of the current state of the art, identify research gaps and future research directions, and facilitate the development of more effective and efficient algorithms for solving this problem. Therefore, this paper aims to conduct a systematic literature review (SLR) of VRPTW-related studies to identify and analyze the major challenges, existing algorithms, evaluation metrics, and potential research directions in this area.

2. Method

The methodology used in this study for conducting a systematic literature review on VRPTW is depicted in Figure 1. To ensure a comprehensive and transparent review, the researchers followed the widely recognized and reliable Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [59]. The PRISMA methodology offers a clear and replicable framework that encompasses literature searches, screening and selection of relevant articles, and synthesis of the findings. The decision to adopt the PRISMA methodology was appropriate for this study as it facilitated a thorough and systematic literature search, a meticulous article screening and selection process, and adherence to a detailed reporting checklist to ensure the review's clarity and transparency.

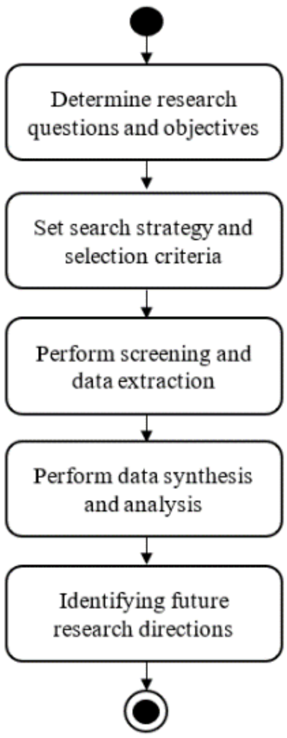

Figure 1. Literature review methodology.

The literature review methodology consists of five sequential steps, which are as follows:

2.1. Determine Research Questions and Objectives

To ensure an organized literature search and analysis, the following research questions and objectives were identified:

Research Questions:

- What are the major challenges and issues faced by VRPTW?
- What are the existing algorithms and solution methods for VRPTW?
- What are the evaluation metrics used to assess the performance of VRPTW algorithms?
- What are the shortcomings and deficiencies of the existing algorithms?
- What are the future research directions and trends in VRPTW?

Research Objectives:

- To provide a comprehensive analysis of the main challenges and issues faced by VRPTW.
- To review and summarize the existing algorithms and solution methods for VRPTW.
- To identify and analyze the evaluation metrics used to assess the performance of VRPTW algorithms.
- To highlight the shortcomings and deficiencies of the existing algorithms and propose potential improvements.
- To identify and discuss the future research directions and trends in VRPTW.

2.2. Determine Search Strategy and Selection Criteria

Several databases, as shown in Table 1, including Science Direct, ACM, Wiley, Springer Link, and IEEE Xplore, were chosen to ensure a comprehensive search of the literature. The chosen search terms were ("vehicle routing problems" OR "VRP" OR "vehicle routing problems with time windows" OR "VRPTW" OR "vehicle routing problems with time window constraints" OR "VRP with time constraints" OR "VRP with time windows" OR "VRP with time constraints" OR "VRP with time window constraints"). The search was conducted on articles published from 2018 until 2022.

Table 1. Websites of databases.

Database	URL
Science Direct	https://www.sciencedirect.com/ (accessed on 30 June 2023)
ACM	https://dl.acm.org/ (accessed on 30 June 2023)
Wiley	https://onlinelibrary.wiley.com/ (accessed on 30 June 2023)
Springer Link	https://link.springer.com/ (accessed on 30 June 2023)
IEEE Xplore	https://ieeexplore.ieee.org/ (accessed on 30 June 2023)

As shown in Table 2, we set inclusion and exclusion criteria for selecting and excluding articles.

Table 2. Eligibility criteria.

Inclusion Criteria	Exclusion Criteria
1. Articles that are peer-reviewed original articles	1. Studies that do not validate the proposed method or algorithm
2. Articles that have a proposed approach for VRPTW	2. Studies offering unclear results or findings
3. Articles that solve the problem of VRPTW and related variants	3. Short papers, posters, short communications, and patents
4. Articles that can access full-text content	4. Duplicated studies (by title or content)
5. Studies written in the English language	5. Articles that were published other than 1 January 2018 to 31 December 2022

Inclusion Criteria: We only included VRPTW-related peer-reviewed research articles that addressed the research questions and objectives defined in Section 2.1. In addition, we considered studies written in English that were available in full-text format.

Exclusion Criteria: We excluded articles that were not related to the VRPTW problems or other variant solutions, such as those that focused on VRPTW evolution, technology, and utilization, or studies that did not validate the proposed method or algorithm, or studies that provided unclear results or findings, or studies that did not meet the inclusion criteria.

2.3. Perform Screening and Data Extraction

The selected studies were evaluated thoroughly during the screening process to assess their relevance to the research questions and objectives. Subsequently, the full-text articles were carefully reviewed, and any studies that failed to meet the inclusion criteria or were not directly related to the research questions were excluded from the analysis. The chosen studies were used to extract the relevant information, which included the research methodologies employed, the types of VRPTW problems examined, and the specific challenges and issues addressed. To identify any common themes, patterns, or gaps in the existing literature, the extracted data was meticulously analyzed.

In our SLR, the screening process was conducted collaboratively by all of the authors. Initially, a comprehensive search was performed to identify relevant papers based on predefined inclusion and exclusion criteria. The selected papers were then distributed among the authors for individual review.

The titles and abstracts of the articles were evaluated independently by each author to determine their relevance to the research questions and objectives. Through this process, the literature was assessed in a comprehensive and unbiased manner.

To ensure the reliability and consistency of the screening process, we adopted a test-retest approach. A random sample of the selected articles was independently reviewed by the same authors at a later stage. This was done to evaluate the consistency and agreement of the inclusion or exclusion decisions made during the initial screening process, following the recommendation by [60] for ensuring quality in the literature reviews.

The responsibilities for conducting the SLR were divided among the authors, with each author actively participating in the screening and data extraction processes. The decisions made during the screening process were based on individual assessments and discussions among the authors to resolve any discrepancies.

2.4. Perform Data Synthesis and Analysis

The findings from the literature review have been carefully presented through a combination of textual narrative, tables, and charts. This approach not only provides a comprehensive and detailed overview of the research, but also allows for a visual representation of the data.

By using tables and charts, important trends and patterns in the research on VRPTW are highlighted in a more digestible and easy-to-understand format. This visual representation adds clarity and depth to the findings, making it easier for readers to grasp the key takeaways from the literature review.

In addition to presenting the synthesized findings, the analysis of the literature has also uncovered common themes and emerging trends in the field of VRPTW. By examining multiple studies and sources, it becomes apparent that certain research directions are more prevalent, indicating areas in which further investigation may be fruitful.

These common themes, patterns, and emerging trends provide valuable insights and guidance for future research in the field of VRPTW. By identifying these areas, researchers can focus their efforts on addressing gaps in the existing literature and exploring new avenues of study.

Overall, the combination of textual narrative, tables, and charts in presenting the synthesized findings, along with the identification of common themes, patterns, and emerging trends, enhances the comprehensiveness and interpretability of the research on VRPTW.

2.5. Identifying Future Research Directions

The analysis of the literature provides a basis for considering potential avenues for future research, which are then presented in the Section 4 of this paper.

3. Result

For a systematic review of VRPTW, Figure 2 depicts the PRISMA flow diagram [59]. Identification, screening, and eligibility are the three stages involved. We obtained 10,556 articles from the database search during the initial identification phase. After removing duplicates, there were 9780 articles left. The screening phase included a review of the article titles and abstracts, which resulted in the inclusion of 344 articles. During the eligibility phase, the remaining articles were subjected to full-text screening, and 280 were rejected because they did not meet the inclusion criteria.

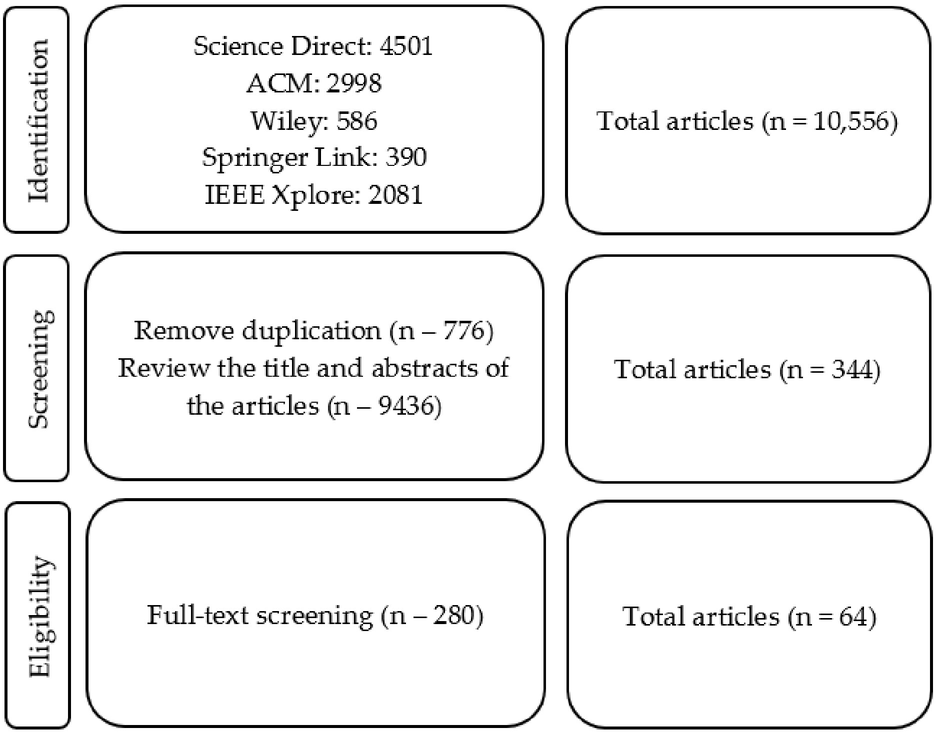

Figure 2. PRISMA flow diagram [59] for systematic review of VRPTW.

The 64 included articles were analyzed and synthesized to provide an overview of the major challenges, existing algorithms, evaluation metrics, and potential research directions in VRPTW (see Supplementary Materials). The findings of our systematic literature review are presented below.

Figure 3 demonstrates the distribution of the number of included studies from 2018 to 2022. It is clear to see that there is a steady sign of increased research on VRPTW. In each of the four years since 2019, more than twice as many articles have been published as in 2018. This shows that VRPTW-related issues have been relatively stable in recent years.

Figure 4 illustrates the number of included studies grouped by journal. It can be seen that the number of articles published in the top three journals, IEEE Access, European Journal of Operational Research, and Applied Soft Computing, accounts for close to 58%. The number of journals that included only one article accounted for more than half of the total.

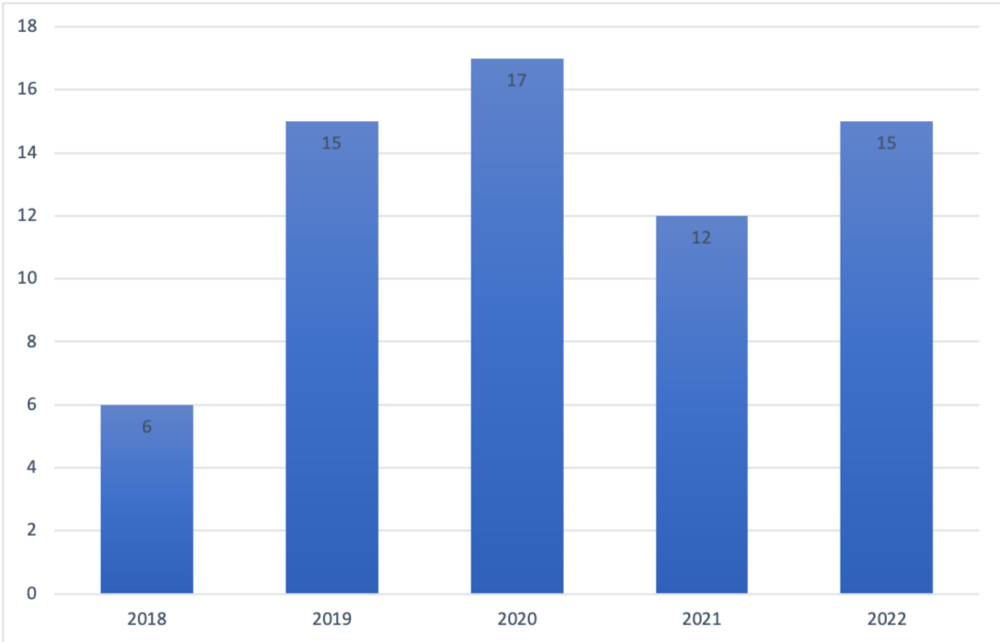

Figure 3. Distribution of papers by year.

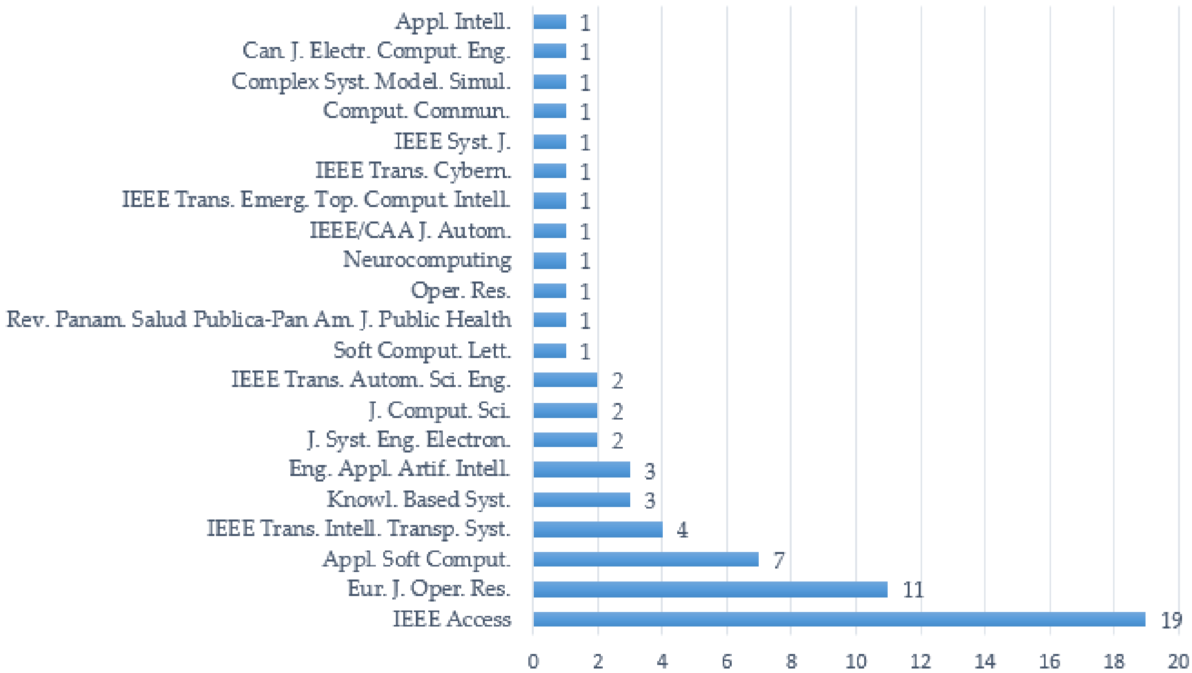

Figure 4. Journal distribution.

Table 3 exhibits details of the included articles and the journals in which they were published. The highest share of the 21 academic journals, nearly 97%, is published in journals owned by IEEE and Elsevier. These two publishers also obtained more results during the initial search phase of the literature (6582, or about 63% of the total). It is noteworthy that one of the journals included in our research comes from the Pan American Health Organization (PAHO). Founded in 1902, it works for the Americas to improve and protect the health of their people. This indicates that the VRPTW issue is of high concern and has an impact worldwide.

Next, we answered the five research questions set out in Section 2.1 in detail, thereby meeting the research objectives we set.

Table 3. Distribution of publication venues.

Journal	Publisher	Articles	Count
Applied Intelligence	Springer	[46]	1
Canadian Journal of Electrical and Computer Engineering-Revure Canadienne De Genie Electrique Et Informatique	IEEE	[25]	1
Complex System Modeling and Simulation	IEEE	[57]	1
Computer Communications	Elsevier	[5]	1
Ieee Systems Journal	IEEE	[61]	1
Ieee Transactions on Cybernetics	IEEE	[18,48]	2
Ieee Transactions on Emerging Topics in Computational Intelligence	IEEE	[10]	1
Ieee-Caa Journal of Automatica Sinica	IEEE	[21]	1
Neurocomputing	Elsevier	[6]	1
Revista Panamericana De Salud Publica-Pan American Journal of Public Health	PAHO	[62]	1
Soft Computing Letters	Elsevier	[63]	1
Ieee Transactions on Automation Science and Engineering	IEEE	[64]	1
Ieee Latin America Transactions	IEEE	[41]	1
Journal of Computational Science	Elsevier	[1,65]	2
Journal of Systems Engineering and Electronics	IEEE	[30,33]	2
Engineering Applications of Artificial Intelligence	Elsevier	[3,15,35]	3
Knowledge-Based Systems	Elsevier	[17,58]	3
Ieee Transactions on Intelligent Transportation Systems	IEEE	[31,44,66]	3
Applied Soft Computing	Elsevier	[2,4,13,34,43,54]	6
European Journal of Operational Research	Elsevier	[12,16,32,36–39,42,49,51,55,56]	12
Ieee Access	IEEE	[7–9,11,14,19,20,22–24,26–29,40,47,50,52,53,67]	19

3.1. Answering Research Question No. 1: What Are the Major Challenges and Issues Faced by VRPTW?

Table 4 summarizes the major challenges and issues faced by VRPTW and its related articles. Here, 87.5% of the articles contained one or more restrictions other than the time window. In addition to the 10 main restrictions, there were several other restrictions that were not recorded. For example, of the other 12.5%, [36] contained the service time restriction and [32] contained the parcel locker restriction. The following are the major challenges and issues faced by VRPTW:

Table 4. A table summarizes the major challenges and issues faced by VRPTW and its related articles.

Article	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Chen et al. (2018) [19]	*	*				*	*			
Chen et al. (2021) [55]	*	*	*	*	*			*		
Ciancio et al. (2018) [56]	*	*	*			*				
Gmira et al. (2021) [57]	*	*			*	*				
Goel and Maini (2018) [25]	*	*	*		*					
Goel et al. (2019) [13]	*	*	*	*	*	*				
Hoogeboom and Dullaert (2019) [14]	*			*		*				
Jie et al. (2022) [54]	*	*	*	*		*				
Liu and Jiang (2019) [53]	*	*	*			*				
Liu et al. (2020) [67]	*	*	*		*					
Lu and Gzara (2019) [35]	*	*			*					
Macrina et al. (2019) [23]	*	*		*	*		*			
Miranda et al. (2018) [26]	*	*	*	*	*	*				
Molina et al. (2020) [24]	*	*			*		*			
Pan et al. (2021) [37]	*		*	*	*					
Reil et al. (2018) [65]	*	*		*	*	*				
Shi et al. (2020) [27]	*	*	*		*			*		
Song et al. (2020) [15]	*	*				*	*			
Wang et al. (2021) [38]	*	*			*		*	*		
Yesodha and Amudha (2022) [28]	*	*	*		*		*			
Exposito-Marquez et al. (2019) [12]	*	*		*	*	*				

Table 4. *Cont.*

Article	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Ali et al. (2021) [20]	*		*							
Fontaine (2022) [16]	*				*					
Sitek et al. (2022) [29]	*	*				*				
Chaieb and Sassi (2021) [21]	*				*	*				
Li et al. (2019) [22]	*	*								
Tilk et al. (2019) [51]	*			*						
Raeesi and Zografos (2021) [64]	*									*
Agrawal et al. (2021) [2]	*	*								
Jiang et al. (2020) [3]	*	*						*		
Lagos et al. (2018) [58]	*							*		
Zheng (2020) [30]	*					*				
Shen et al. (2020) [44]	*									
Jiang et al. (2020) [61]	*					*				
Duan et al. (2022) [63]	*					*				
Dekhici et al. (2019) [4]	*					*				
Deng et al. (2018) [52]	*							*		
Wang et al. (2019) [39]	*					*				
Wu et al. (2020) [6]	*								*	
Zhang et al. (2020) [31]	*							*		
Shen et al. (2022) [66]	*			*						*
Mao et al. (2020) [48]	*									*
Shen et al. (2021) [68]	*					*				*
Yan et al. (2019) [69]	*								*	
He et al. (2021) [43]	*									
Li and Li (2020) [36]	*									
Wu et al. (2019) [40]	*									
Khoo et al. (2020) [46]	*									
Zhang et al. (2018) [45]	*									
Yu et al. (2022) [49]	*									
Lin et al. (2022) [50]	*									*
Yu et al. (2022) [32]	*									
Liu et al. (2022) [47]	*			*						
Lan et al. (2020) [33]	*					*				
Riazi et al. (2019) [5]	*									
Zhang et al. (2020) [7]	*	*								
Zhu et al. (2021) [34]	*									*
Sun et al. (2019) [41]	*							*		
Zhou et al. (2019) [8]	*									*
Wang et al. (2020) [42]	*					*		*		
Liu and Wang (2022) [9]	*	*				*				
Perboli et al. (2021) [17]	*			*						
Li et al. (2022) [10]	*				*					
Miguel et al. (2019) [18]	*	*			*	*				

Note: C1–C10 refer to the 10 challenges and issues mentioned earlier. * denotes that the article addresses the corresponding challenge or issue.

Time windows (C1): Time windows are a critical aspect of VRPTW as they limit the delivery or pickup times for each customer. However, they also add complexity to the problem and make it difficult to find optimal solutions.

Capacitated vehicles (C2): The capacity of the vehicles used in VRPTW is limited, which means that a vehicle may not be able to serve all customers in a single trip. This adds complexity to the problem as it requires efficient vehicle routing and scheduling.

Heterogeneous fleet (C3): In some cases, VRPTW involves a heterogeneous fleet of vehicles with different capacities and capabilities. This makes it challenging to optimize vehicle routing and scheduling.

Dynamic demand (C4): In some applications, customer demand may be dynamic and uncertain. This makes it difficult to plan the vehicle routes and schedules in advance.

Travel time (C5): The travel time between the customers and depots is an important factor in VRPTW, as it affects the overall efficiency of the delivery or pickup process. However, factors such as traffic congestion and road conditions may have an impact on travel time.

Multi-objective optimization (C6): VRPTW often involves multiple objectives, such as minimizing the total travel time or distance, maximizing vehicle utilization, and minimizing the number of vehicles used. These conflicting objectives make it challenging to find optimal solutions.

Environmental considerations (C7): In recent years, there has been a growing emphasis on reducing the environmental impact of transportation. VRPTW needs to consider environmental factors such as vehicle emissions and energy consumption while optimizing vehicle routing and scheduling.

Pickup and delivery (C8): In many logistics and transport tasks, the customers have demands for delivery and pickup. For pick-up and delivery within the time range, each customer is allocated a certain window of time.

Time-dependent (C9): For modern logistics, sometimes vehicles need to complete their travel routes within a certain time limit.

Electric Vehicles (C10): In contrast with combustion-engine vehicles, electric vehicles are unable to complete long-distance deliveries due to their limited battery capacity. If necessary, they need to travel to a limited number of charging stations and then charge for a period of time.

Of the above 64 papers, the 10 most cited between 2018 and 2022 are shown in Table 5. From these 10 papers, we can see that in the last five years, researchers focused more on the use of metaheuristics, especially a mixture of two or more algorithms to solve multi-objective or multi-constrained tasks. Among them, route planning for electric vehicles is more complex and difficult compared with conventional fuel vehicles. Notably, the VRPTW problem is more targeted and applied to the real-world logistics and transportation industries.

Table 5. Top 10 most cited articles.

Article	Citations
Goel & Maini (2018) [25]	82
Macrina et al. (2019) [23]	75
Wang et al. (2019) [39]	71
Liu et al. (2020) [67]	56
Gmira et al. (2021) [57]	52
Reil et al. (2018) [65]	48
Pan et al. (2021) [37]	46
Wang et al. (2020) [42]	43
Chen et al. (2021) [55]	42
Song et al. (2020) [15]	34

3.2. *Answering Research Question No. 2: What Are the Existing Algorithms and Solution Methods for VRPTW?*

Table 6 shows the algorithms and solution methods used in the review articles for the VRPTW problem. We categorized the algorithms and solution methods into five main groups: exact, heuristic, metaheuristic, hybrid, and other methods.

Table 6. Summary of the existing algorithms and solution methods for VRPTW.

Article	Exact Method	Heuristic Method	Metaheuristic Method	Hybrid Method	Other Method
Chen et al. (2018) [19]			LS and ALNS		Ruin-and-recreate based
Chen et al. (2021) [55]		ALNS			
Ciancio et al. (2018) [56]	BPC				
Exposito-Marquez et al. (2019) [12]		GRASP			
Gmira et al. (2021) [57]			TS		
Goel and Maini (2018) [25]			ACO and FA	HAFA	
Hoogeboom and Dullaert (2019) [14]			TS	Hybrid	

Table 6. *Cont.*

Article	Exact Method	Heuristic Method	Metaheuristic Method	Hybrid Method	Other Method
Goel et al. (2019) [13]			ACO		
Jie et al. (2022) [54]			GA and VNS	Hybrid	
Liu et al. (2020) [67]				CAATD	
Liu and Jiang (2019) [53]		LNS		H-LNS	
Lu and Gzara (2019) [35]	BPC				
Macrina et al. (2019) [23]			GA		
Miranda et al. (2018) [26]			NSGA-II		
Molina et al. (2020) [24]		B&C			
Pan et al. (2021) [37]			GRASP and SA		
Reil et al. (2018) [65]	BPC		BPPA		
Shi et al. (2020) [27]				LBTS	
Song et al. (2020) [15]			GA and ACO	Hybrid	
Wang et al. (2021) [38]			GA and VNS	Hybrid	
Yesodha and Amudha (2022) [28]			FA		
Ali et al. (2021) [20]			ALNS		
Fontaine, (2022) [16]			ALNS		
Sitek et al. (2020) [29]			GA		
Chaieb and Sassi (2021) [21]			TS		
Li et al. (2019) [22]			FA		
Tilk et al. (2019) [51]		BPAC			
Raeesi and Zografos (2021) [64]		MG-DP-ILNS			
Jiang et al. (2020) [3]			ACO	Hybrid	
Lagos et al. (2018) [58]			PSO		
Zheng (2020) [30]			IA		
Shen et al. (2020) [44]			ACO and BSO	Hybrid	
Jiang et al. (2020) [61]			VNS		
Duan et al. (2022) [63]			PSO		
Dekhici et al. (2019) [4]			FA		
Deng et al. (2018) [52]			ACO and MMAS	Hybrid	
Wang et al. (2019) [39]		MOEA			
Wu et al. (2020) [6]			TS		
Zhang et al. (2020) [31]		DMMA			
Shen et al. (2022) [66]			ALNS		
Mao et al. (2020) [48]		LS	ACO	Hybrid	
Shen et al. (2021) [68]		EDA	LFD	Hybrid	
Yan et al. (2019) [69]		INDS and INS		Hybrid	
He et al. (2021) [43]			ACO and VNS	Hybrid	
Li and Li (2020) [36]			TS		
Wu et al. (2019) [40]			BSO and ACO	Hybrid	
Khoo et al. (2020) [46]			GA		Ruin-and-recreate based
Zhang et al. (2018) [45]			GA and PSO	Hybrid	Ruin-and-recreate based
Yu et al. (2022) [49]	CGA		PSO	Hybrid	
Lin et al. (2022) [50]					DRL
Yu et al. (2022) [32]			SA		
Liu et al. (2022) [47]			BSO and ACO	Hybrid	
Lan et al. (2020) [33]			VNS		Decomposition-based
Riazi et al. (2019) [5]	CGA			Hybrid	Gossip algorithm
Zhang et al. (2020) [7]			SA		
Zhu et al. (2021) [34]			GA		
Sun et al. (2019) [41]			TS and ALNS	Hybrid	
Zhou et al. (2019) [8]			G and NS	Hybrid	

Table 6. *Cont.*

Article	Exact Method	Heuristic Method	Metaheuristic Method	Hybrid Method	Other Method
Wang et al. (2020) [42]			ILS	Hybrid	
Liu and Wang (2022) [9]			ALNS		
Perboli et al. (2021) [17]		LNS			
Li et al. (2022) [10]			LS and SA	Hybrid	
Miguel et al. (2019) [18]			MOEA	Hybrid	
Agrawal et al. (2020) [2]			CI		

Note: ACO: ant colony optimization; ALNS: adaptive large neighborhood search; ANS: adaptive neighborhood selection; BPC: branch-and-price-and-cut; BSO: brain storm optimization; CGA: column generation algorithm; CI: cohort intelligence algorithm; DMMA: dynamic memory memetic algorithm; DRL: deep reinforcement learning; EDA: estimation of distribution algorithm; FA: firefly algorithm; G: greedy algorithm; GA: genetic algorithm; GRASP: greedy randomized adaptive search procedure; IA: Ito algorithm; IDNS: iteratively dynamic neighborhood search; ILS: iterated local search; INS: iterative neighborhood search; LFD: Lévy flight distribution; LNS: large neighborhood search; LS: local search; MG-DP-ILNS: multi-graph dynamic programming based intensified large neighborhood search; MMAS: max − min ant system; MOEA: multi-objective evolutionary algorithm; PSO: particle swarm optimization; RBP: robust branch-and-price; SA: simulated annealing; TS: Tabu Search; VND: variable neighborhood descent; VNS: variable neighborhood search.

Exact Method: Refers to algorithms that guarantee the optimal solution to a problem. To the best of our knowledge, most of these methods are limited to solve instances of small to medium-sized VRPTW where the exact solution can be found within a reasonable amount of time. These methods include techniques such as direct tree search methods (e.g., branch-and-price-and-cut) and dynamic programming.

Heuristic Method: Refers to algorithms that are designed to quickly find a good solution but do not guarantee the optimal solution. These methods are often used for larger instances of VRPTW, where exact algorithms are computationally expensive. These methods include techniques such as constructive heuristics, the savings algorithm, and the Clarke and Wright Algorithm.

Metaheuristic Method: Refers to algorithms that are designed to efficiently search through large solution spaces to find good-quality solutions. These methods often combine multiple heuristic techniques to create a robust search strategy. These methods include techniques such as simulated annealing, Tabu search, genetic algorithm, ant colony optimization, and particle swarm optimization.

Hybrid Method: Refers to algorithms that combine two or more techniques from the other categories to create a more powerful search strategy. These methods often combine exact and heuristic techniques, or heuristic and metaheuristic techniques, to find high-quality solutions in a reasonable amount of time.

Other Method: Refers to approaches that do not fit into any of the other categories. These methods may include techniques such as constraint programming, integer programming, and artificial neural networks. These methods are often used to solve specific VRPTW problems, such as those with time-dependent or stochastic travel times.

Table 6 shows that most articles use heuristic and metaheuristic methods to solve the VRPTW problem. Exact methods are used less frequently because the VRPTW is known to be an NP-hard problem, which makes finding exact solutions computationally expensive for larger instances. Hybrid methods and other methods are used less frequently but still have some representation in the literature. Figure 5 illustrates the details of the usage of the method types. Approximate algorithms accounted for over three-quarters of the total, with metaheuristics exceeding heuristics in approximate algorithms, accounting for 69% and 17%, respectively. Exact algorithms accounted for just under 10%, at 7%. For other methods, deep reinforcement learning accounted for 7% of the total.

Figure 6 and Table 6 show the taxonomy of VRPTW algorithms and highlight the wide variety of approaches that researchers have taken to address the complex and challenging VRPTW problem, demonstrating the significant effort and ingenuity that have gone into this field of research, respectively. Moreover, the ongoing evolution of the field suggests that new and innovative algorithms and solution methods will continue to emerge, pushing the boundaries of what is possible and driving further advancements in VRPTW research. As a result, the impact of this research will likely extend far beyond the academic community as its findings and insights are applied to real-world transportation and logistics challenges, helping to optimize and streamline the delivery of goods and services, while minimizing costs and environmental impact.

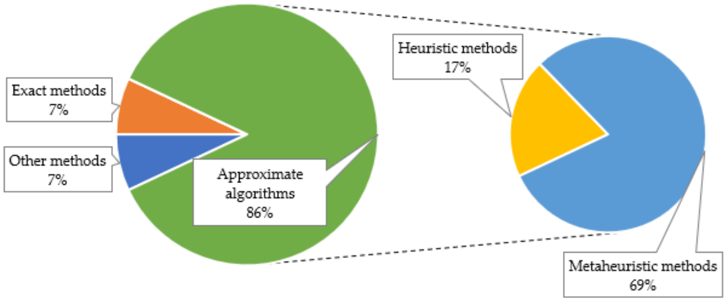

Figure 5. Method used for solving the VRPTW problem.

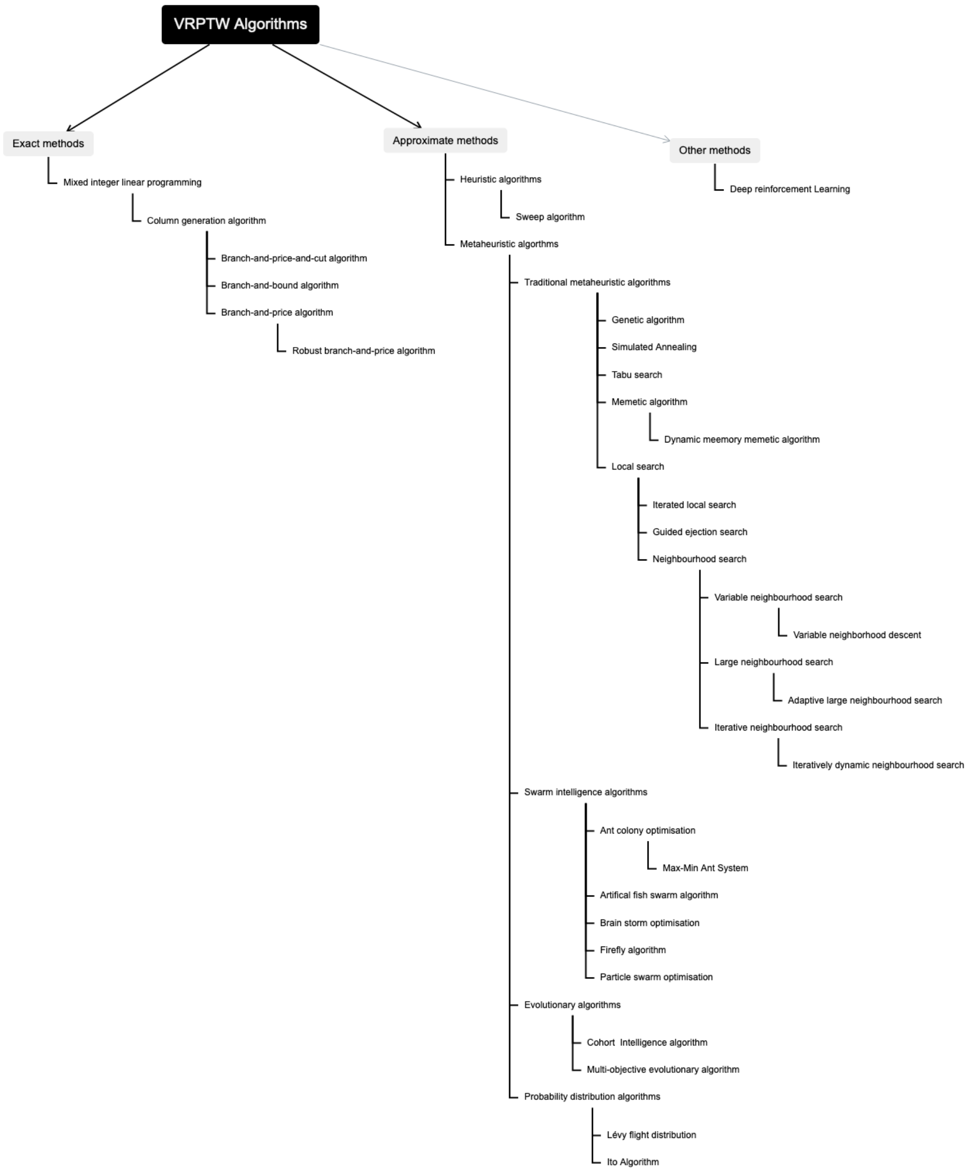

Figure 6. Taxonomy of VRPTW algorithms.

In recent years, a large number of algorithms have been proposed to solve the VRPTW family of problems. Based on the 64 papers reviewed in this paper, the commonly used algorithms fall into three main categories: exact algorithms, approximate algorithms, and other algorithms. As shown in Figure 5, the most adopted algorithm in the last five years has been the approximation algorithm. In particular, there are far more metaheuristic algorithms among them than heuristic algorithms. Notably, there have been attempts to introduce deep reinforcement learning algorithms, popular in other computer-related fields, to solve the VRPTW family of problems.

3.3. Answering Research Question No. 3: What Are the Evaluation Metrics Used to Assess the Performance of VRPTW Algorithms?

Table 7 provides a comprehensive overview of the evaluation metrics used to measure the performance of VRPTW algorithms. These metrics are classified into four categories: solution quality, computational time, convergence, and diversity.

Table 7. Summary of the evaluation metrics and formulae used to assess the performance of VRPTW.

Metric	Formula	Description
Total Travel Distance	$\sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}x_{ij}$	Total distance traveled by all vehicles
Total Travel Time	$\sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}x_{ij}$	Total time taken to travel all routes
Number of Vehicles Used	$\sum_{i=1}^{m} y_i$	Number of vehicles used to serve all customers
Maximum Vehicle Load	$\max_{i=1}^{m} \sum_{j=1}^{n} q_j x_{ij}$	Maximum load of any vehicle
Average Vehicle Load	$(\sum_{i=1}^{m}\sum_{j=1}^{n} q_j x_{ij})/(\sum_{i=1}^{m} y_i)$	Average load of all vehicles
Route Duration Variance	$\frac{1}{m}\sum_{i=1}^{m}(T_i - \overline{T})^2$	Variance of the duration of all routes
Route Duration Standard Deviation	$\sqrt{\frac{1}{m}\sum_{i=1}^{m}(T_i - \overline{T})^2}$	Standard deviation of the duration of all routes
Time Window Violations	$\sum_{i=1}^{n}(max(0, t_i - a_i) + max(0, b_i - t_i))$	Total time window violations across all customers
Feasibility Ratio	(Number of feasible solutions)/(Total number of solutions)	Ratio of feasible solutions to the total number of solutions
Computation Time	-	Time taken to find a solution

Note: n: The number of customers; m: The number of vehicles; q: The capacity of each vehicle; d_{ij}: The distance between customer i and customer j; c_i: The demand of customer i; t_i: The time window for customer i, specified as a time interval $[a_i, b_i]$; s_i: The service time required at customer i; p_i: The pickup quantity for customer i; r_i: The delivery quantity for customer i; t_{ij}: The travel time between customer i and customer i; f_{ij}: The fuel consumption between customer i and customer j; s_{ij}: The carbon emission between customer i and customer j; T_i: The arrival time at customer i; V_k: The total distance traveled by vehicle k; C: The total cost of the solution, including fuel consumption and vehicle usage cost; O: The objective function being optimized, such as minimizing the total distance traveled or the total cost of the solution; z: The best-known solution for a given problem instance; z': The solution obtained by the algorithm being evaluated; CPU: The CPU time required to solve the problem instance; Gap: The relative gap between the best-known solution and the solution obtained by the algorithm, expressed as a percentage; It: The number of iterations required by the algorithm to converge to a solution.

The solution quality metrics assess the quality of the obtained solutions in terms of the number of vehicles used, total distance traveled, total travel time, total waiting time, maximum lateness, and total cost. These metrics provide insights into the efficiency of the algorithms regarding resource utilization, distances covered, time spent traveling and waiting, delivery punctuality, and overall cost effectiveness.

The computational time metrics evaluate the efficiency of the algorithms in terms of the time required to find the best solution, the time taken to find the first feasible solution, and the average time per iteration. These metrics help determine how quickly the algorithms can generate feasible solutions and their overall computational efficiency.

The convergence metrics measure the speed and efficiency of the algorithms in converging to optimal or near-optimal solutions. The metrics include convergence speed, the number of iterations required for convergence, and the convergence rate. These metrics provide insights into the algorithms' ability to converge and find optimal solutions within a reasonable timeframe.

Lastly, the diversity metrics focus on evaluating the diversity of the solutions produced by the algorithms. These metrics encompass the entropy of the solutions and the diversity of the solutions. By measuring the entropy, these metrics assess the randomness or variability of the solutions found, while the diversity metric quantifies the number of distinct solutions obtained.

In summary, Table 7 offers a valuable reference for evaluating the performance of VRPTW algorithms. It enables researchers and practitioners to compare different algorithms by analyzing their results for each metric. This table is an indispensable resource for assessing and understanding the effectiveness of various algorithms in solving VRPTW problems.

3.4. Answering Research Question No. 4: What Are the Shortcomings and Deficiencies of the Existing Algorithms?

There are several shortcomings and deficiencies in the existing algorithms for solving VRPTW problems. Some of these include the following:

Inability to handle large problem instances: Many existing algorithms are not capable of handling large problem instances with many customers, vehicles, and time windows. This is because these algorithms often have high computational complexity, and their running times increase exponentially with problem size. For example, exact algorithms, such as branch and bound, can become computationally infeasible for large problem instances. In addition, many heuristic and metaheuristic algorithms can become stuck in local optima for large problems.

Lack of scalability: Related to the first point, many existing algorithms do not scale well with problem size. As the problem size increases, the solution quality may degrade significantly, or the algorithm may become infeasible due to its computational complexity. For example, some algorithms may be efficient for small to medium-sized problems, but their performance may degrade quickly for large problems.

Difficulty in handling stochasticity: Many VRPTW problems are subject to stochasticity, such as uncertainty in customer demand or travel times. However, many existing algorithms do not explicitly handle stochasticity or do so in a limited manner. For example, some algorithms may assume deterministic customer demands and travel times, which can result in suboptimal solutions when these assumptions are violated.

Lack of flexibility: Many existing algorithms are tailored to specific problem formulations or assumptions, such as fixed fleet sizes or uniform vehicle capacities. This can limit their applicability to real-world problems that may have varying or dynamic constraints. For example, an algorithm designed for VRPTW with a fixed fleet size may not be suitable for problems with a flexible fleet size.

Dependence on problem-specific heuristics: Some existing algorithms rely on problem-specific heuristics or techniques, which may limit their applicability to other VRPTW problems. For example, an algorithm that relies on specific properties of the problem, such as a certain network structure or vehicle capacity distribution, may not be suitable for problems that violate these assumptions.

Limited comparison to state-of-the-art: Many existing algorithms are evaluated against a limited set of benchmarks or other algorithms, which may limit the generalizability of their results. For example, an algorithm may perform well against a few benchmark problems, but may not perform well against more challenging problems or other state-of-the-art algorithms.

Overall, while existing VRPTW algorithms have made significant progress in addressing the complexities and challenges of these problems, there is still much room for improvement in terms of scalability, flexibility, and handling stochasticity. Future research could focus on developing more efficient and flexible algorithms that can handle stochasticity and can be applied to a wide range of VRPTW problems.

3.5. Answering Research Question No. 5: What Are the Future Research Directions and Trends in VRPTW?

There are several potential future research directions and trends in VRPTW, including:

Exact algorithms: Based on the reviewer's comment, exact algorithms such as branch and price (BP), branch and cut (BC), and branch-and-price-and-cut (BPC) play a crucial role in solving vehicle routing problems (VRP), including the VRP with time windows (VRPTW), and are indeed a significant field of study.

Branch and price (BP) and branch and cut (BC) are exact algorithms that combine the principles of branch-and-bound and column generation techniques to solve combinatorial optimization problems efficiently. These algorithms decompose the problem into subproblems, iteratively branching on the solution space and generating columns (routes in VRP context) to improve the lower bounds and find better feasible solutions.

Branch and price (BP) typically applies to problems with a large number of variables (e.g., VRP with many customers) and a smaller number of constraints (e.g., capacity and time window constraints). On the other hand, branch and cut (BC) is more suitable for problems with a large number of constraints, and it involves cutting planes to tighten the problem's relaxation.

Branch-and-price-and-cut (BPC) is an extension that combines the advantages of both BP and BC. It integrates column generation with cutting planes to efficiently solve large-scale combinatorial optimization problems such as VRP. BPC allows for the dynamic addition of new columns (routes) and cutting planes (constraints) during the search process, which helps to improve the solution quality and convergence speed.

Hybridization of algorithms: Hybridizing two or more algorithms can help leverage the strengths of each algorithm and create more powerful solutions. For example, a hybrid algorithm could combine the local search capabilities of tabu search with the global optimization capabilities of genetic algorithms.

Integration of machine learning: Machine learning algorithms such as the deep Q network (DQN) algorithm [70] can be used to develop predictive models that can improve the accuracy of demand forecasting, route optimization, and other aspects of VRPTW. For example, a neural network could be used to predict the demand or availability profiles for each customer based on historical data, such as failed delivery data [71], which could then be used to optimize the routes to reduce the chance of failed delivery.

Real-time decision-making: With the advent of the Internet of Things (IoT) and real-time data analytics, it may be possible to make more informed and dynamic decisions in real time. For example, sensors on delivery vehicles could transmit data about traffic, weather, and other factors that could be used to optimize routes in real time.

Multi-objective optimization: Multi-objective optimization is an approach to optimization that considers multiple conflicting objectives simultaneously. For example, in VRPTW, one objective may be to minimize travel time, while another may be to minimize transportation costs [72], such as fuel consumption. Multi-objective optimization can help find trade-offs between conflicting objectives and identify optimal solutions. Another example is when a branch-and-cut algorithm was combined with price to create a branch-and-price-and-cut algorithm to avoid freight consolidation and storage without increasing its transportation cost [73].

Green VRPTW or Electric VRPTW [74]: With increasing concern about environmental sustainability, there is a growing interest in developing "green" VRPTW algorithms that minimize carbon emissions and energy consumption. For example, an algorithm such as mixed-integer linear programming [75] could optimize routes based on the availability of charging stations for electric vehicles.

Collaborative VRPTW: Collaborative VRPTW involves the coordination of multiple vehicles, such as ride-hailing vehicles and electric motorcycles [76], from multiple companies or organizations to optimize delivery routes. For example, a collaborative VRPTW algorithm could optimize the routes of several delivery companies that operate in the same area to minimize congestion and reduce delivery times.

Autonomous delivery: With the development of autonomous vehicles and drones, there is a growing interest in developing VRPTW algorithms that can optimize the routes of autonomous vehicles [77]. For example, an algorithm could optimize the routes of a fleet of autonomous delivery vehicles to minimize delivery times and maximize efficiency.

4. Conclusions

This systematic literature review (SLR) provides a targeted and comprehensive overview of the Vehicle Routing Problems with Time Windows (VRPTW) family of literature published from 2018 to 2022. Following the PRISMA systematic literature review guidelines, we formulated five research questions and objectives, searched 10,556 VRPTW-related papers from reputable databases, and identified 64 articles that met our criteria. The entire review process adhered closely to the PRISMA guidelines, ensuring replicability.

The findings of this study indicate that the multi-objective and/or multi-constrained VRPTW problem has been the most interesting area of research for the research community in the last five years. The majority of research in this field has focused on approximation algorithms, accounting for 86% of all algorithms investigated. Notably, algorithms such as the Adaptive Large Neighborhood Search (ALNS) have shown effectiveness in solving large-scale VRPTW problems. The ALNS algorithm's ability to adaptively explore different neighborhoods makes it well-suited for handling large problem instances. We acknowledge the value of ALNS and its potential for addressing VRPTW challenges. Additionally, we understand that the branch-and-price-and-cut (BPC) algorithm can also be employed to solve large-scale VRPTW problems. Some robust VRP algorithms cover stochasticity, and some dynamic VRP algorithms focus on flexible fleet sizes. However, our review of the literature indicated that the ALNS and BPC algorithms may have limitations when applied to larger problem instances, as suggested by studies [56,65], while flexible fleet size is mentioned as a goal or constraint in the literature [22,41,61].

Our SLR also speculates on potential future research directions, including the hybridization of algorithms, integration into machine learning, real-time decision making, multi-objective optimization, electric vehicles, collaborative VRPTW, and automated delivery. These directions highlight the evolving nature of the field and the need to address emerging challenges and opportunities.

Considering the context of intelligent transportation systems (ITS) and smart vehicles, the integration of VRPTW algorithms becomes increasingly relevant. By incorporating real-time data and leveraging advanced technologies, such as autonomous capabilities and vehicle-to-infrastructure communication, VRPTW algorithms can optimize routes, minimize travel time, and reduce costs. The utilization of smart vehicles equipped with intelligent features further enhances the efficiency and effectiveness of logistics and transportation operations.

This SLR contributes to the understanding of VRPTW algorithms and their potential applications in the context of ITS and smart vehicles. By harnessing real-time data and advanced algorithms, logistics and transportation systems can achieve improved resource utilization, reduced congestion, and enhanced overall performance. The findings underscore the significance of integrating VRPTW solutions within the framework of ITS and leveraging smart vehicles for future advancements in this field.

5. Limitation

One potential limitation of the paper is the potential for publication bias. The review focused on articles published in specific databases and may have missed relevant studies published in other sources or unpublished works. This could introduce a bias in the findings and limit the comprehensiveness of the review.

Another limitation is the restriction to a specific time period, with the review encompassing studies published only within the last five years. While this approach allows for a focused analysis of recent research, it may exclude relevant studies published before the defined time frame that could provide valuable insights or historical context.

Additionally, the review's reliance on the accuracy and completeness of the selected articles is another potential limitation. The quality of the review is dependent on the quality of the included studies, and there is a possibility of incomplete reporting or biases within the selected articles that could impact the overall findings and conclusions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151512004/s1, PRISMA Abstract Checklist. Reference [59] is cited in the Supplementary Materials.

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References

1. Solomon, M.M. Algorithms for the vehicle routing and scheduling problems with time window constraints. *Oper. Res.* **1987**, *35*, 254–265. [CrossRef]
2. Agrawal, P.; Kaur, G.; Kolekar, S.S. Investigation on biomedical waste management of hospitals using cohort intelligence algorithm. *Soft Comput. Lett.* **2021**, *3*, 100008. [CrossRef]
3. Jiang, P.; Men, J.; Xu, H.; Zheng, S.; Kong, Y.; Zhang, L. A Variable Neighborhood Search-Based Hybrid Multiobjective Evolutionary Algorithm for HazMat Heterogeneous Vehicle Routing Problem With Time Windows. *IEEE Syst. J.* **2020**, *14*, 4344–4355. [CrossRef]
4. Dekhici, L.; Redjem, R.; Belkadi, K.; Mhamedi, A.E. Discretization of the firefly algorithm for home care. *Can. J. Electr. Comput. Eng.* **2019**, *42*, 20–26. [CrossRef]
5. Riazi, S.; Wigström, O.; Bengtsson, K.; Lennartson, B. A column generation-based gossip algorithm for home healthcare routing and scheduling problems. *IEEE Trans. Autom. Sci. Eng.* **2019**, *16*, 127–137. [CrossRef]
6. Wu, Y.; Zheng, B.; Zhou, X.L. A disruption recovery model for time-dependent vehicle routing problem with time windows in delivering perishable goods. *IEEE Access* **2020**, *8*, 189614–189631. [CrossRef]
7. Zhang, S.Q.; Mu, D.; Wang, C. A Solution for the Full-Load Collection Vehicle Routing Problem With Multiple Trips and Demands: An Application in Beijing. *IEEE Access* **2020**, *8*, 89381–89394. [CrossRef]
8. Zhou, F.L.; He, Y.D.; Zhou, L. Last Mile Delivery With Stochastic Travel Times Considering Dual Services. *IEEE Access* **2019**, *7*, 159013–159021. [CrossRef]
9. Liu, R.S.; Wang, N. Data-Driven Bus Route Optimization Algorithm Under Sudden Interruption of Public Transport. *IEEE Access* **2022**, *10*, 5250–5263. [CrossRef]
10. Li, X.; Gao, J.; Wang, C.; Huang, X.; Nie, Y. Ride-Sharing Matching Under Travel Time Uncertainty Through Data-Driven Robust Optimization. *IEEE Access* **2022**, *10*, 116931–116941. [CrossRef]
11. Sun, Q.; Chien, S.; Hu, D.; Chen, G.; Jiang, R.-S. Optimizing Multi-Terminal Customized Bus Service With Mixed Fleet. *IEEE Access* **2020**, *8*, 156456–156469. [CrossRef]
12. Expósito, A.; Brito, J.; Moreno, J.A.; Expósito-Izquierdo, C. Quality of service objectives for vehicle routing problem with time windows. *Appl. Soft Comput.* **2019**, *84*, 105707. [CrossRef]
13. Goel, R.; Maini, R.; Bansal, S. Vehicle routing problem with time windows having stochastic customers demands and stochastic service times: Modelling and solution. *J. Comput. Sci.* **2019**, *34*, 1–10. [CrossRef]
14. Hoogeboom, M.; Dullaert, W. Vehicle routing with arrival time diversification. *Eur. J. Oper. Res.* **2019**, *275*, 93–107. [CrossRef]

15. Song, M.-X.; Li, J.-Q.; Han, Y.Q.; Han, Y.-Y.; Liu, L.-L.; Sun, Q. Metaheuristics for solving the vehicle routing problem with the time windows and energy consumption in cold chain logistics. *Appl. Soft Comput.* **2020**, *95*, 106561. [CrossRef]
16. Fontaine, P. The vehicle routing problem with load-dependent travel times for cargo bicycles. *Eur. J. Oper. Res.* **2022**, *300*, 1005–1016. [CrossRef]
17. Perboli, G.; Rosano, M.; Wei, Q. A Simulation-Optimization Approach for the Management of the On-Demand Parcel Delivery in Sharing Economy. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 10570–10582. [CrossRef]
18. Miguel, F.; Frutos, M.; Tohmé, F.; Babey, M.M. A Decision Support Tool for Urban Freight Transport Planning Based on a Multi-Objective Evolutionary Algorithm. *IEEE Access* **2019**, *7*, 156707–156721. [CrossRef]
19. Chen, B.; Qu, R.; Bai, R.; Laesanklang, W. A hyper-heuristic with two guidance indicators for bi-objective mixed-shift vehicle routing problem with time windows. *Appl. Intell.* **2018**, *48*, 4937–4959. [CrossRef]
20. Ali, O.; Cote, J.F.; Coelho, L.C. Models and algorithms for the delivery and installation routing problem. *Eur. J. Oper. Res.* **2021**, *291*, 162–177. [CrossRef]
21. Chaieb, M.; Ben, D. Sassi, Measuring and evaluating the Home Health Care Scheduling Problem with Simultaneous Pick-up and Delivery with Time Window using a Tabu Search metaheuristic solution. *Appl. Soft Comput.* **2021**, *113*, 107957. [CrossRef]
22. Li, J.; Li, T.; Yu, Y.; Zhang, Z.; Pardalos, P.M.; Zhang, Y.; Ma, Y. Discrete firefly algorithm with compound neighborhoods for asymmetric multi-depot vehicle routing problem in the maintenance of farm machinery. *Appl. Soft Comput.* **2019**, *81*, 105460. [CrossRef]
23. Macrina, G.; Laporte, G.; Guerriero, F.; Pugliese, L.D.P. An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows. *Eur. J. Oper. Res.* **2019**, *276*, 971–982. [CrossRef]
24. Molina, J.C.; Salmero, J.L.; Eguia, I.; Racero, J. The heterogeneous vehicle routing problem with time windows and a limited number of resources. *Eng. Appl. Artif. Intell.* **2020**, *94*, 103745. [CrossRef]
25. Goel, R.; Maini, R. A hybrid of ant colony and firefly algorithms (HAFA) for solving vehicle routing problems. *J. Comput. Sci.* **2018**, *25*, 28–37. [CrossRef]
26. Miranda, D.M.; Branke, J.; Conceicao, S.V. Algorithms for the multi-objective vehicle routing problem with hard time windows and stochastic travel time and service time. *Appl. Soft Comput.* **2018**, *70*, 66–79. [CrossRef]
27. Shi, Y.; Zhou, Y.; Boudouh, T.; Grunder, O. A lexicographic-based two-stage algorithm for vehicle routing problem with simultaneous pickup-delivery and time window. *Eng. Appl. Artif. Intell.* **2020**, *95*, 103901. [CrossRef]
28. Yesodha, R.; Amudha, T. A bio-inspired approach: Firefly algorithm for Multi-Depot Vehicle Routing Problem with Time Windows. *Comput. Commun.* **2022**, *190*, 48–56. [CrossRef]
29. Sitek, P.; Wikarek, J.; Rutczyńska-Wdowiak, K.; Bocewicz, G.; Banaszak, Z. Optimization of capacitated vehicle routing problem with alternative delivery, pick-up and time windows: A modified hybrid approach. *Neurocomputing* **2021**, *423*, 670–678. [CrossRef]
30. Zheng, J. A Vehicle Routing Problem Model With Multiple Fuzzy Windows Based on Time-Varying Traffic Flow. *IEEE Access* **2020**, *8*, 39439–39444. [CrossRef]
31. Zhang, H.; Wang, Z.; Tang, M.; Lv, X.; Luo, H.; Liu, Y. Dynamic Memory Memetic Algorithm for VRPPD With Multiple Arrival Time and Traffic Congestion Constraints. *IEEE Access* **2020**, *8*, 167537–167554. [CrossRef]
32. Yu, V.F.; Susanto, H.; Jodiawan, P.; Ho, T.-W.; Lin, S.-W.; Huang, Y.-T. A Simulated Annealing Algorithm for the Vehicle Routing Problem With Parcel Lockers. *IEEE Access* **2022**, *10*, 20764–20782. [CrossRef]
33. Lan, Y.-L.; Liu, F.; Ng, W.W.Y.; Zhang, J.; Gui, M. Decomposition Based Multi-Objective Variable Neighborhood Descent Algorithm for Logistics Dispatching. *IEEE Trans. Emerg. Top. Comput. Intell.* **2021**, *5*, 826–839. [CrossRef]
34. Zhu, Y.F.; Lee, K.Y.; Wang, Y.H. Adaptive Elitist Genetic Algorithm With Improved Neighbor Routing Initialization for Electric Vehicle Routing Problems. *IEEE Access* **2021**, *9*, 16661–16671. [CrossRef]
35. Lu, D.; Gzara, F. The robust vehicle routing problem with time windows: Solution by branch and price and cut. *Eur. J. Oper. Res.* **2019**, *275*, 925–938. [CrossRef]
36. Li, G.M.; Li, J.H. An Improved Tabu Search Algorithm for the Stochastic Vehicle Routing Problem With Soft Time Windows. *IEEE Access* **2020**, *8*, 158115–158124. [CrossRef]
37. Pan, B.B.; Zhang, Z.Z.; Lim, A. Multi-trip time-dependent vehicle routing problem with time windows. *Eur. J. Oper. Res.* **2021**, *291*, 218–231. [CrossRef]
38. Wang, Y.; Li, Q.; Guan, X.; Fan, J.; Xu, M.; Wang, H. Collaborative multi-depot pickup and delivery vehicle routing problem with split loads and time windows. *Knowl. Based Syst.* **2021**, *231*, 107412. [CrossRef]
39. Wang, J.H.; Weng, T.Y.; Zhang, Q.F. A Two-Stage Multiobjective Evolutionary Algorithm for Multiobjective Multidepot Vehicle Routing Problem With Time Windows. *IEEE Trans. Cybern.* **2019**, *49*, 2467–2478. [CrossRef]
40. Wu, L.; He, Z.; Chen, Y.; Wu, D.; Cui, J. Brainstorming-Based Ant Colony optimization for Vehicle Routine With Soft Time Windows. *IEEE Access* **2019**, *7*, 19643–19652. [CrossRef]
41. Sun, B.; Yang, Y.; Shi, J.; Zheng, L. Dynamic Pick-Up and Delivery Optimization With Multiple Dynamic Events in Real-World Environment. *IEEE Access* **2019**, *7*, 146209–146220. [CrossRef]
42. Wang, J.; Sun, Y.; Zhang, Z.; Gao, S. Solving multitrip pickup and delivery problem with time windows and manpower planning using multiobjective algorithms. *IEEE/CAA J. Autom.* **2020**, *7*, 1134–1153. [CrossRef]
43. He, M.; Wei, Z.; Wu, X.; Peng, Y. An Adaptive Variable Neighborhood Search Ant Colony Algorithm for Vehicle Routing Problem With Soft Time Windows. *IEEE Access* **2021**, *9*, 21258–21266. [CrossRef]

44. Shen, Y.; Liu, M.; Yang, J.; Shi, Y.; Middendorf, M. A Hybrid Swarm Intelligence Algorithm for Vehicle Routing Problem With Time Windows. *IEEE Access* **2020**, *8*, 93882–93893. [CrossRef]
45. Zhang, J.T.; Yang, F.X.; Weng, X. An Evolutionary Scatter Search Particle Swarm Optimization Algorithm for the Vehicle Routing Problem With Time Windows. *IEEE Access* **2018**, *6*, 63468–63485. [CrossRef]
46. Khoo, T.-S.; Mohammad, B.B.; Wong, V.-H.; Tay, Y.-H.; Nair, M. A Two-Phase Distributed Ruin-and-Recreate Genetic Algorithm for Solving the Vehicle Routing Problem With Time Windows. *IEEE Access* **2020**, *8*, 169851–169871. [CrossRef]
47. Liu, M.; Song, Q.; Zhao, Q.; Li, L.; Yang, Z.; Zhang, Y. A Hybrid BSO-ACO for Dynamic Vehicle Routing Problem on Real-World Road Networks. *IEEE Access* **2022**, *10*, 118302–118312. [CrossRef]
48. Mao, H.; Shi, J.; Zhou, Y.; Zhang, G. The Electric Vehicle Routing Problem With Time Windows and Multiple Recharging Options. *IEEE Access* **2020**, *8*, 114864–114875. [CrossRef]
49. Yu, N.; Qian, B.; Hu, R.; Chen, Y.; Wang, L. Solving open vehicle problem with time window by hybrid column generation algorithm. *J. Syst. Eng. Electron.* **2022**, *33*, 997–1009. [CrossRef]
50. Lin, B.; Ghaddar, B.; Nathwani, J. Deep Reinforcement Learning for the Electric Vehicle Routing Problem With Time Windows. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 11528–11538. [CrossRef]
51. Tilk, C.; Drexl, M.; Irnich, S. Nested branch-and-price-and-cut for vehicle routing problems with multiple resource interdependencies. *Eur. J. Oper. Res.* **2019**, *276*, 549–565. [CrossRef]
52. Deng, Y.; Zhu, W.; Li, H.; Zheng, Y. Multi-type ant system algorithm for the time dependent vehicle routing problem with time windows. *J. Syst. Eng. Electron.* **2018**, *29*, 625–638.
53. Liu, R.; Jiang, Z.B. A hybrid large-neighborhood search algorithm for the cumulative capacitated vehicle routing problem with time-window constraints. *Appl. Soft Comput.* **2019**, *80*, 18–30. [CrossRef]
54. Jie, K.W.; Liu, S.Y.; Sun, X.J. A hybrid algorithm for time-dependent vehicle routing problem with soft time windows and stochastic factors. *Eng. Appl. Artif. Intell.* **2022**, *109*, 104606. [CrossRef]
55. Chen, C.; Demir, E.; Huang, Y. An adaptive large neighborhood search heuristic for the vehicle routing problem with time windows and delivery robots. *Eur. J. Oper. Res.* **2021**, *294*, 1164–1180. [CrossRef]
56. Ciancio, C.; Lagana, D.; Vocaturo, F. Branch-price-and-cut for the Mixed Capacitated General Routing Problem with Time Windows. *Eur. J. Oper. Res.* **2018**, *267*, 187–199. [CrossRef]
57. Gmira, M.; Gendreau, M.; Lodi, A.; Potvin, J.-Y. Tabu search for the time-dependent vehicle routing problem with time windows on a road network. *Eur. J. Oper. Res.* **2021**, *288*, 129–140. [CrossRef]
58. Lagos, C.; Guerrero, G.; Cabrera, E.; Moltedo, A.; Johnson, F.; Paredes, F. An improved Particle Swarm Optimization Algorithm for the VRP with Simultaneous Pickup and Delivery and Time Windows. *IEEE Lat. Am. Trans.* **2018**, *16*, 1732–1740. [CrossRef]
59. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Rev. Panam. Salud Publica-Pan Am. J. Public Health* **2022**, *46*, e112.
60. Kitchenham, B.; Charters, S. Guidelines for Performing Systematic Literature Reviews in Software Engineering; Technical Report EBSE 2007-001, Keele University and Durham University Joint Report. 2007. Available online: https://www.elsevier.com/__data/promis_misc/525444systematicreviewsguide.pdf (accessed on 20 June 2023).
61. Jiang, G.; Lam, S.-K.; Ning, F.; He, P.; Xie, J. Peak-Hour Vehicle Routing for First-Mile Transportation: Problem Formulation and Algorithms. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 3308–3321. [CrossRef]
62. Paul, A.; Kumar, R.S.; Rout, C.; Goswami, A. A bi-objective two-echelon pollution routing problem with simultaneous pickup and delivery under multiple time windows constraint. *OpSearch* **2021**, *58*, 962–993. [CrossRef]
63. Duan, J.H.; He, Z.A.; Yen, G.G. Robust Multiobjective Optimization for Vehicle Routing Problem With Time Windows. *IEEE Trans. Cybern.* **2022**, *52*, 8300–8314. [CrossRef] [PubMed]
64. Raeesi, R.; Zografos, K.G. Coordinated routing of electric commercial vehicles with intra-route recharging and en-route battery swapping. *Eur. J. Oper. Res.* **2022**, *301*, 82–109. [CrossRef]
65. Reil, S.; Bortfeldt, A.; Monch, L. Heuristics for vehicle routing problems with backhauls, time windows, and 3D loading constraints. *Eur. J. Oper. Res.* **2018**, *266*, 877–894. [CrossRef]
66. Shen, Y.; Yu, L.; Li, J. Robust Electric Vehicle Routing Problem with Time Windows under Demand Uncertainty and Weight-Related Energy Consumption. *Complex Syst. Model. Simul.* **2022**, *2*, 18–34. [CrossRef]
67. Liu, C.; Kou, G.; Zhou, X.; Peng, Y.; Sheng, H.; Alsaadi, F.E. Time-dependent vehicle routing problem with time windows of city logistics with a congestion avoidance approach. *Knowl. Based Syst.* **2020**, *188*, 104813. [CrossRef]
68. Shen, Y.D.; Peng, L.W.; Li, J. An improved estimation of distribution algorithm for multi-compartment electric vehicle routing problem. *J. Syst. Eng. Electron.* **2021**, *32*, 365–379.
69. Yan, X.; Xiao, B.; Xiao, Y.; Zhao, Z.; Ma, L.; Wang, N. Skill vehicle routing problem with time windows considering dynamic service times and time-skill-dependent costs. *IEEE Access* **2019**, *7*, 77208–77221. [CrossRef]
70. Ahamed, T.; Zou, B.; Farazi, N.P.; Tulabandhula, T. Deep reinforcement learning for crowdsourced urban delivery. *Transp. Res. B Methodol.* **2021**, *152*, 227–257. [CrossRef]
71. Voigt, S.; Frank, M.; Fontaine, P.; Kuhn, H. The Vehicle Routing Problem with Availability Profiles. *Transp. Sci.* **2022**, *57*, 531–551. [CrossRef]

72. Sahin, M.K.; Yamana, H. A Branch and Price Algorithm for the Heterogeneous Fleet Multi-Depot Multi-Trip Vehicle Routing Problem with Time Windows. *Transp. Sci.* **2022**, *56*, 1409–1722. [CrossRef]
73. Marques, G.; Sadykov, R.; Dupas, R.; Deschamps, J.-C. A Branch-Cut-and-Price Approach for the Single-Trip and Multi-Trip Two-Echelon Vehicle Routing Problem with Time Windows. *Transp. Sci.* **2022**, *56*, 1598–1617. [CrossRef]
74. Froger, A.; Jabali, O.; Mendoza, J.E.; Laporte, G. The Electric Vehicle Routing Problem with Capacitated Charging Stations. *Transp. Sci.* **2022**, *56*, 460–482. [CrossRef]
75. Montoya, A.; Gueret, C.; Mendoza, J.E.; Villegas, J.G. The electric vehicle routing problem with nonlinear charging function. *Transp. Res. B Methodol.* **2017**, *103*, 87–110. [CrossRef]
76. Zhan, X.; Szeto, W.Y.; Wang, Y. The ride-hailing sharing problem with parcel transportation. *Transp. Res. E Logist. Transp. Rev.* **2023**, *172*, 103073. [CrossRef]
77. Guo, Q.; Ban, X.J. A multi-scale control framework for urban traffic control with connected and automated vehicles. *Transp. Res. B Methodol.* **2023**, *175*, 102787. [CrossRef]