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A Survey on Variable Neighborhood Search for Sustainable Logistics

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Abstract: Sustainable logistics aims to balance economic efficiency, environmental responsibility, and social well-being in supply chain operations. This study explores the use of Variable Neighborhood Search (VNS), a metaheuristic optimization method, in addressing sustainable logistics challenges and provides insights into the potential it has to support them by delivering efficient solutions that align with global sustainability goals. The review identifies key trends, including a significant increase in research since 2019, with a strong focus on routing, scheduling, and location problems. Hybrid approaches, combining VNS with other methods, and multiobjective optimization to address trade-offs between sustainability goals are prominent. The most frequently applied VNS versions align closely with those commonly used in the broader literature, reflecting similar adoption proportions. In recent years, a noticeable increase in studies incorporating adaptation mechanisms into VNS frameworks has emerged. This trend is largely driven by the growing influence of Artificial Intelligence approaches across numerous fields of science and engineering, highlighting the need for more dynamic and intelligent optimization techniques. However, important research gaps remain. These include limited consideration of uncertainty and dynamic logistics systems, underrepresentation of social sustainability, and a lack of standardized benchmarks for comparing results. Future work should address these challenges and explore emerging applications.

Keywords: variable neighborhood search; VNS; sustainable logistics

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1. Introduction

Logistics plays a crucial role in modern economies by facilitating the movement and storage of goods, services, and information from their point of origin to their point of consumption, with the primary goal of satisfying customer or business requirements. It involves the strategic planning, implementation, and control of various interconnected activities, such as transportation, warehousing, inventory management, and coordination of supply chains. These functions are essential to ensuring timely delivery, optimizing resource utilization, maintaining cost efficiency, and improving overall service levels.

In recent years, the concept of sustainability has become increasingly integrated into logistics practices, driven by the need for businesses to meet the growing consumer demand for environmentally friendly products and services, as well as to comply with stricter environmental regulations worldwide. Sustainable logistics is a broader concept that refers to the management and optimization of supply chain processes in a way that minimizes environmental impact, promotes social responsibility, and ensures economic viability.

The challenge lies in balancing these three pillars of sustainability—economic, environmental, and social—while maintaining high levels of service and efficiency. Sustainable logistics encompasses a range of initiatives aimed at reducing carbon emissions, implementing eco-friendly transportation methods, optimizing resource utilization, and minimizing waste, all while ensuring that businesses continue to thrive in an increasingly competitive market.

The goal of sustainable logistics is to create a harmonious balance between economic growth, environmental stewardship, and social well-being. It requires careful consideration of immediate and long-term impacts on the environment, society, and economy. By optimizing logistics processes through sustainable practices, businesses can not only reduce their ecological footprint but also contribute to broader global sustainability goals. In the context of this study, the three key dimensions of sustainability are defined as follows:

- Economic sustainability refers to the ability of an economic system to support long-term growth while ensuring the efficient use of resources and financial stability. It requires careful management to avoid negative impacts on social, environmental, or cultural factors. It emphasizes the efficient allocation of resources to ensure that industries, businesses, and economies can continue to function in a sustainable manner, while also providing opportunities for future generations to prosper.
- Environmental sustainability focuses on managing and conserving natural resources in a responsible manner to prevent ecosystem degradation and ensure that these resources remain available for future generations. This dimension of sustainability involves reducing pollution, conserving biodiversity, minimizing waste, and promoting renewable energy sources and sustainable practices in industries such as transportation, manufacturing, and agriculture. The ultimate objective is to protect the health of the planet and maintain its ecological balance for the well-being of future generations.
- Social sustainability is about creating and maintaining societies that promote social equity, justice, and well-being for all individuals. This pillar focuses on ensuring access to basic services such as education, healthcare, and employment opportunities, as well as fostering inclusive and resilient communities. Social sustainability emphasizes the importance of respecting human rights, cultural diversity, and social progress, ensuring that future generations inherit a world characterized by equality, fairness, and peace.

These three pillars are deeply interconnected and often contradictory. For example, efforts to reduce environmental impacts might increase short-term costs, while focusing on social well-being may complicate economic efficiency. To address these complexities, a system's approach is essential, one that acknowledges the dynamic interplay and trade-offs among these dimensions. In addition, sustainability is closely aligned with the principles of a circular economy, which seeks to minimize waste and optimize resource utilization across the entire value chain—from production to consumption. By closing the loop through strategies such as recycling, reuse, and remanufacturing, the circular economy supports the Sustainable Development Goals (SDGs) adopted by the United Nations [1,2]. These goals emphasize rational resource use, reduced environmental impact, and improved social well-being. Embedding such principles into sustainable logistics not only addresses immediate challenges but also creates long-term strategies for resilient and efficient systems.

Given the growing importance of sustainable logistics, optimization techniques like Variable Neighborhood Search (VNS) have gained attention in recent years due to their ability to solve complex, combinatorial optimization problems. VNS is a powerful metaheuristic framework widely used for solving large-scale global optimization problems across various domains, including logistics. It operates by systematically exploring different neighborhood structures to diversify the search and enhance intensification, making it highly effective in identifying high-quality solutions. VNS has shown particular promise

in solving logistics-related problems, where finding optimal or near-optimal solutions is critical to improving efficiency, minimizing costs, and achieving sustainability goals.

The connection between VNS and sustainable logistics lies in its ability to address the three core dimensions of sustainability—economic, environmental, and social—through optimization techniques. VNS contributes to sustainable logistics by enabling decision-makers to optimize critical operations, such as minimizing carbon emissions in transportation, reducing energy consumption in warehouses, and improving resource allocation across supply chains. Moreover, its capacity to handle multiobjective problems, especially when it is hybridized with other optimization methods, ensures that economic efficiency can be balanced with environmental and social considerations, such as integrating renewable energy sources into logistics networks or improving worker welfare.

VNS can also guide the development of sustainable logistics goals by offering a structured approach to explore and evaluate potential trade-offs between conflicting objectives. For instance, it can prioritize solutions that reduce costs while maintaining low environmental impacts, thus supporting organizations in meeting sustainability targets. Additionally, the adaptability of VNS allows it to incorporate specific constraints and scenarios, such as uncertainty in demand or dynamic changes in logistics networks, making it a practical and versatile tool for achieving long-term sustainability goals.

The versatility and robustness of VNS make it an ideal tool for addressing the optimization challenges that arise in sustainable logistics, particularly those that involve complex decision-making, such as routing, scheduling, and location. By applying VNS to these logistics problems, it is possible to simultaneously consider economic, environmental, and social factors, providing solutions that balance efficiency with sustainability. Furthermore, VNS can be adapted and hybridized with other optimization methods to enhance its effectiveness in solving multiobjective problems, which is particularly relevant in sustainable logistics, where multiple conflicting objectives must be considered.

This study aims to investigate the use of VNS in sustainable logistics in a deeper way by addressing the following key research questions:

- In which specific areas of sustainable logistics is VNS most commonly applied, and what types of problems does it address most effectively?
- Which VNS variants are utilized most frequently to solve these sustainable logistics problems?
- How is VNS commonly hybridized with other optimization methods to tackle complex logistics challenges, and which hybridization approaches have proven to be the most effective?
- How are multiobjective logistics problems, which often involve trade-offs between different sustainability aspects, addressed when employing VNS?
- Which aspects of sustainability are most frequently considered when applying VNS to solve logistics problems, and how are these aspects integrated into the optimization process?

By answering these questions, this study will contribute to the growing body of knowledge regarding the use of VNS in sustainable logistics, integrating economic, environmental, and social dimensions of sustainability. Unlike existing reviews that primarily focus on specific VNS variants or isolated applications, our work takes a holistic approach, identifying trends, challenges, and opportunities across multiple facets of sustainable logistics, such as routing, scheduling, and supply chain design. The findings will provide valuable insights into the application of VNS in various logistics challenges and how it can be leveraged to enhance sustainability in logistics operations. Additionally, we highlight the growing importance of adaptive and hybrid VNS methods in addressing the dynamic and multiobjective nature of logistics problems. By systematically categorizing and analyzing

the literature, this study not only offers new insights into the current state of VNS research but also identifies critical gaps and provides actionable recommendations for future work.

The remainder of this article is structured as follows. Section 2 provides a detailed description of the VNS methodology, including its key versions and extensions. Section 3 outlines the review methodology used in this study, detailing the steps taken to identify the relevant literature and analyze the results. Section 4 presents the findings of the literature review, focusing on the main applications, hybridizations, and sustainability considerations associated with VNS in sustainable logistics. Section 5 presents a discussion highlighting the research trends, challenges, and gaps identified in the reviewed literature and offers directions for future research. Section 6 presents a discussion on advantages, limitations, and decisions when implementing VNS for sustainable logistics. Finally, Section 7 concludes the article with a summary of key insights and their implications for both research and practice in sustainable logistics optimization.

2. VNS: Concept, Versions, and Extensions

VNS is a metaheuristic proposed by Nenad Mladenović in 1995 [3], whose key idea was to apply systematic changes in the neighborhood structure during search. The metaheuristic framework was first formalized in 1997 in joint works with Pierre Hansen [4,5]. The principles of this metaheuristic were established in 2001 [6]. VNS has played an important role in the field of metaheuristics and its applications [7–9]. This metaheuristic and its versions have been applied to a large series of optimization problems and most logistic problems since the beginning of the century [9,10]. These versions appear considering variations of their components and the inclusion of another ingredient in the framework [11]. It has three main components: a shaking method, an improvement procedure, and a neighborhood change strategy [7]. The main versions are the Basic VNS (BVNS), the Reduced VNS (RVNS), the Variable Neighborhood Descent (VND), the General VNS (GVNS), and the Adaptive VNS (AVNS).

The BVNS proposal consists of using a series of neighborhood structures to shake the incumbent solution, a local search to improve it, and the sequential change strategy for the neighborhood structure. Each neighborhood structure is given by a specific set of moves that can be applied to a solution; the neighborhood of that solution is constituted by the solutions that can be obtained by applying one of these moves. The shaking of a solution consists of selecting a random solution from its neighborhood. The sequential strategy consists of selecting the next neighborhood structure of the series if there is no improvement in the best solution found so far and starting with the first structure of the series otherwise. Therefore, starting from the initial solution as the current solution, the procedure shakes and applies the local search to the current. The change strategy is applied until no improvement in the best solution is obtained with the last structure of the series.

RVNS is a very simple proposal that consists of excluding the improvement step in BVNS [7]. An RVNS method is obtained when no local search is applied after shaking the current solution, i.e., selecting the next neighborhood structure of the series if the shaking solution does not improve the best solution found so far and starting with the first structure of the series otherwise. VND is the variant that appears by applying the core VNS idea of a sequential change in the neighborhood structure to a neighborhood-based local search.

GVNS is one of the most widely used versions of VNS [7]. This variant is obtained from BVNS, using a VND as the improvement step. The series of neighborhoods used in the shaking phase and in the VND could be the same, but usually they are different because their purposes are different. Different versions of VNS appear by considering variations of these proposals and the inclusion of another ingredient in the framework [11].

As a result of the current tendency, the relevance of Artificial Intelligence (AI) approaches in science and technology has the effect of using adaptive tools in optimization search [8]. AVNS is the result of the incorporation of an adaptive mechanism into some of the components of a VNS, mainly in the way of ordering the neighborhoods or when they are selected. The first explicit proposals of an AVNS are in [12,13]. From the BNS, the AVNS obtained consists of using an adaptive mechanism in the shaking phase by favoring moves or neighborhoods according to their success within the search. This approach is used in sustainable logistics in [14–18]. A second way is to select the neighborhood for the improvement procedure, usually in a VND, based on its performance during the search process that is applied to sustainable logistics in [19–21]. The adaptation strategy can be applied in a GVNS in both the shaking phase and improvement phase and is used in sustainable logistics by [22], but most articles use it only in the shaking phase of the GVNS [23–25]. Other adaptive strategies used with VNS in sustainable logistics are in a hybrid way, such as with a Genetic Algorithm (GA) [19,26], Particle Swarm Optimization (PSO) [27], an Electro-Magnetism Algorithm (EMA) [28], or an Artificial Bee Colony (ABC) [29,30]. Another way to use adaptivity in VNS using sustainable logistics, such as in [31], is with a mechanism that automatically chooses between the first improvement and the best improvement strategies in the improvement phase of VNS (see [32]).

Other variants of VNS have few applications in sustainable logistics. The Skewed VNS (SVNS) is the version introduced by [33], where a move to a worse solution is admitted if it is only "slightly" worse and "sufficiently" distant from the current solution. Condition $f(x') < f(x)$ is replaced by $f(x') < f(x) - \alpha\delta(x', x)$ for the appropriate value α and the function $\delta(.,.)$. Parallel BVNS with SVNS are applied in network design for reverse logistics in [34] and in [35] for a routing problem minimizing emissions. A Skewed GVNS (SGVNS) is applied to solve a battery swap station location/routing problem with capacitated electric vehicles in [36]. SVNS is also applied to sustainable logistics in [37,38].

In the Variable Neighborhood Decomposition Search (VNDS) variant proposed in [6], after shaking the incumbent solution by changing some of its attributes, the local search works on the subproblem containing only the attributes that have been changed while keeping the remaining ones fixed. The size of the subproblem plays the role of the shaking neighborhood parameter. No publications on the application of VNDS in sustainable logistics have been found in the literature. The VNS Branching proposed by [39] is applied in [40] to an electric vehicle routing problem with time windows.

The simplest version of VNS is the Fixed Neighborhood Search (FNS), which considers a single neighborhood structure in the shake procedure and for the local search [41] and coincides with the first variant of the Iterated Local Search [42]. This method is applied in [43] to a routing distribution problem with drones. The Nested VNS (NVNS) consists of applying a VNS procedure to the solutions of a predefined neighborhood structure, rather than only to an initial solution [44,45]. If the main loop also uses VNS, the procedure is referred to as a two-level GVNS [46]. Some combinations of VNS variants could also be used, such as a General VNDS or a Skewed General VNDS [8], by replacing VNS with VNDS in GVNS or SGVNS, respectively. In the reviewed literature, no publications have been found on the application of these VNS variants in sustainable logistics.

3. Review Methodology

To address the research questions outlined in the previous section, a Systematic Literature Review (SLR) was performed to provide a thorough and detailed analysis of the current state of the art. This study followed the guidelines proposed by [47,48] to conduct an SLR. The methodology of this study comprises six steps:

- Formulation of the search question and choice of keywords.

- Definition of inclusion and extrusion criteria.
- Search in databases.
- Paper selection; discussion and analysis of the results.
- Reporting of the results.

In the following, we detail each of these steps.

3.1. Question Formulation and Keywords Definition

The first step in this review is the definition of the research questions. In this regard, the aim of this research is to examine the existing state of the art dealing with sustainable logistics problems using VNS and to examine in which areas of logistics this metaheuristic has been applied most frequently and successfully, as well as to identify the most commonly used version and understand how it has been implemented.

Based on the research purpose, we have defined a list of keywords in order to localize and limit this study. In addition to *Variable Neighborhood Search* and *VNS*, we have considered two sets of keywords: those related to sustainability and those related to logistics. The first set contains the following: *green*, *sustainable*, *environmental*, *closed-loop*, *reverse*, *electric*, *emissions*, *energy consumption*, *waste collection*, and *wind farm*. The second set contains the following: *logistics*, *transportation*, *supply chain*, *location*, *inventory*, and *scheduling*. We have included the keyword *waste collection* in our search because waste management is a critical aspect of sustainability in logistics. Efficient waste collection systems directly contribute to reducing environmental impact by optimizing waste transport and disposal. In the context of sustainable logistics, the use of advanced optimization techniques like VNS can significantly enhance the efficiency of waste collection processes, making them more environmentally friendly and cost-effective. Regarding the keyword *wind farm*, we have included it because wind farms play a significant role in the transition to renewable energy, which is a key component of sustainable logistics. Optimizing the logistics associated with wind farm operations, such as the transportation and installation of wind turbines, can lead to significant improvements in efficiency and sustainability. The application of VNS to wind farm-related logistics problems helps minimize transport costs, reduce emissions, and enhance the overall effectiveness of renewable energy projects.

3.2. Definition of Inclusion and Exclusion Criteria

In addition to the keywords identified in the initial step, we established a list of inclusion and exclusion criteria to refine the literature search and determine the articles to focus on. Table 1 presents these criteria.

Table 1. Inclusion and exclusion criteria used to select papers.

	Criteria	**Justification**
Inclusion	Papers published between 2006 and August 2024	To focus on the most recent publications.
	Publications in peer-reviewed journals, conference papers and chapters	To concentrate on high-quality articles and other documents for a broader and more comprehensive literature search.
	The measure of environmental or social impact is explicit either in the objective function or in the constraints of the model, or comes implicitly due to the kind of vehicles used (electric, hybrid, . . .)	This criterion ensures that the research specifically addresses sustainability aspects, which is central to our study. By including models that consider environmental or social impacts, we can better evaluate the effectiveness and practicality of various logistics solutions in promoting sustainable practices. The focus on vehicle types further emphasizes the operational choices that contribute to reduced emissions and overall environmental benefits.

Table 1. *Cont.*

	Criteria	Justification
Exclusion	Studies in a language other than English	English is the predominant language of scientific research, ensuring a wider scope of high-quality and peer-reviewed papers. Additionally, limiting the review to English-language papers facilitates consistent and accurate analysis by all researchers involved.

3.3. Search in Databases

Once the keywords and criteria have been defined, the next step is the selection of the databases and the definition of the queries to be considered. We have selected the following source databases: Google Scholar, Web of Science, and Scopus. They have been chosen due to their comprehensive coverage of high-quality, peer-reviewed literature in the fields of logistics, optimization, and sustainability, as well as their global recognition as leading academic research platforms. We then started a data search of the various databases identified by creating the following query:

("variable neighborhood search" OR vns) AND (green OR sustainable OR environmental OR "closed-loop" OR reverse OR electric OR emissions OR "energy consumption" OR "waste collection" OR "wind farm") AND (logistics OR transportation OR "supply chain" OR location OR inventory OR scheduling)

In Web of Science and Scopus, each term of queries was searched in the title, abstract, and keywords. At this point, we identified a first set of articles based on the relevance of the title according to the context of the study. A total of 226 articles were identified.

3.4. The Selection of the Most Relevant Papers

By implementing our inclusion and exclusion criteria, we identified the most pertinent studies for our focus and excluded those that were not relevant. During the selection process, we thoroughly reviewed the full text of each article and examined their references to conduct a secondary search. Subsequently, we included papers that were initially missed in our database search. Ultimately, a total of 171 papers were selected for review and analysis as key studies.

We recognize the following potential limitations of this review. While our review focused on peer-reviewed journals and conferences to ensure the reliability and rigor of the included studies, this approach may inadvertently exclude relevant unpublished or non-peer-reviewed work, such as technical reports or gray literature. Although peer review is a hallmark of quality, it may also contribute to underrepresentation of unconventional or preliminary research that could still hold value for this field. Regarding the database coverage, although we used leading databases, we acknowledge that no database can provide complete coverage of all relevant literature. Finally, despite a systematic approach, our focus on studies published in English and those directly addressing the integration of sustainability aspects into VNS applications may have excluded relevant contributions in other languages or related domains.

3.5. Analysis, Synthesis, and Results Reporting: Classification Methodology

After the relevant papers have been identified, steps 5 and 6 focus on synthesizing the literature and reporting the results. Each paper was thoroughly reviewed by both authors, and the fields presented in the table in Appendix A, along with two additional fields—the name of the journal and the year of publication—were extracted. These fields were carefully chosen to capture the most relevant aspects of VNS usage and its connection to sustainable logistics. Once all this information was collected, it enabled the authors to calculate the number of articles published per year, the distribution of articles across journals, and other

statistical analyses used in the survey. This systematic approach ensured that the data were synthesized accurately and that the results presented are both reliable and representative of the field.

First, a descriptive analysis of the selected literature was performed, examining the distribution of the work over time and across various journals. In line with the research questions outlined in the first step, the papers were categorized based on the specific decision problems they addressed. Later, we deepen descriptions of the versions of the VNS used, the hybridization of the VNS with other methods, the multiobjective problems and approaches to solve it using VNS, and the uncertain and dynamics aspects considered. Finally, we present an analysis of the sustainability criteria.

In the subsequent sections, we conduct this thorough analysis of the literature identified based on the aforementioned categorizations. This enables us to ascertain the current trends about the use of VNS in sustainable logistics and identify research gaps in this field.

4. Results and Findings

Figure 1 illustrates the growth in the number of papers related to the topic of this study. As shown, there has been a significant increase in publications since 2019, underscoring the growing importance of VNS in the field of sustainable logistics. Note that the year 2024 presents a small decrease due to the date of the present study.

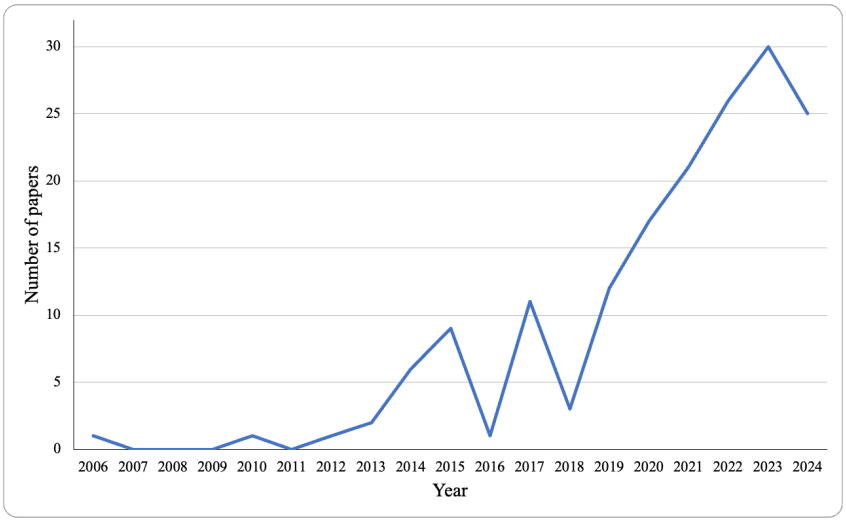


Figure 1. Number of publications per year.

Regarding the journals where these studies are published, most of them belong to the areas of operations research, computer science, and engineering. The two most frequent journals are *Computers & Operations Research* and *Computers & Industrial Engineering*. Figure 2 shows the concept cloud created according to the number of papers published in each journal.

In terms of the optimization problem addressed, we have identified five primary types: routing, location, scheduling, location/routing, scheduling/routing, and network design. Additionally, a few papers focus on smaller categories such as inventory, lot sizing, and layout, which have been grouped under the category "Others". As shown in Figure 3, the vast majority of papers using variants of VNS for sustainable logistics deal with routing problems, followed by scheduling.

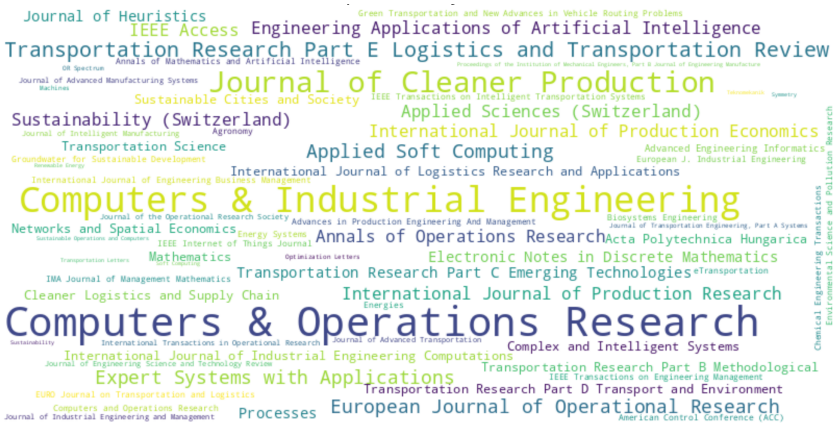


Figure 2. A cloud of concepts with the journals according to the papers.

In the following sections, we provide a more detailed analysis of the hybridization of VNS with other methods, explore multiobjective approaches that incorporate VNS, examine the consideration of uncertainty and dynamism in the studies, and conclude with an analysis of sustainability. For a more synthesized analysis, Appendix A includes a summary of the papers selected in this review and its characteristics.

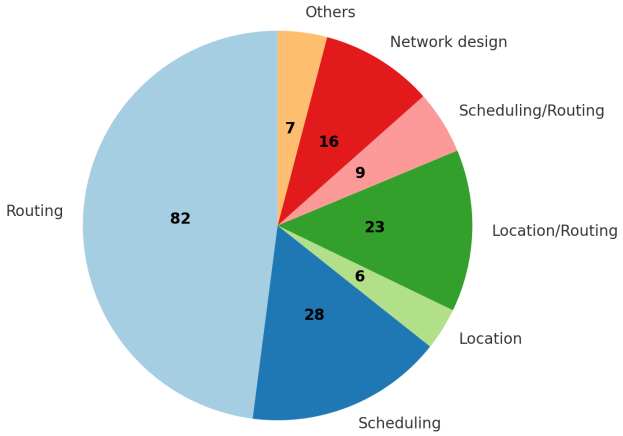


Figure 3. Number of publications per general decision problem.

4.1. VNS Version Analysis

A search on Scopus for the term "Variable Neighborhood Search" yields over 3000 works referencing this metaheuristic. However, many of these works do not explicitly mention the specific version of VNS used, making it necessary to perform a detailed content analysis to determine the version applied. Among the explicitly mentioned versions, BVNS is identified in approximately 80 articles. However, as observed in this study on sustainable logistics, it is likely that many of the works that do not specify a version implicitly use the basic version. The most frequently cited variant is VND, appearing in 540 articles. This popularity is due to its natural derivation from local search methods when different types of movements are considered. GVNS is explicitly mentioned in 213 works, while RVNS appears in 88. Notably, adaptive versions of VNS, such as AVNS or AGVNS, are referenced in 40 studies, with a significant concentration in recent years. Other notable variants include VNDS (37 articles) and SVNS (26 articles). Similar trends are reported in other surveys on VNS applications [49,50], further confirming these observations.

As illustrated in Figure 4, the most widely used VNS variants in sustainable logistics are BVNS and GVNS. VND is also frequently applied, as it naturally extends local search methods by incorporating changes in the movement applied. Several studies have used

RVNS, which simplifies the search process by omitting the local search component. In recent years, the adaptability of metaheuristic designs has led to the emergence of various AVNS proposals. Other VNS versions have been applied in a limited number of studies, reflecting their more specialized or niche use cases.

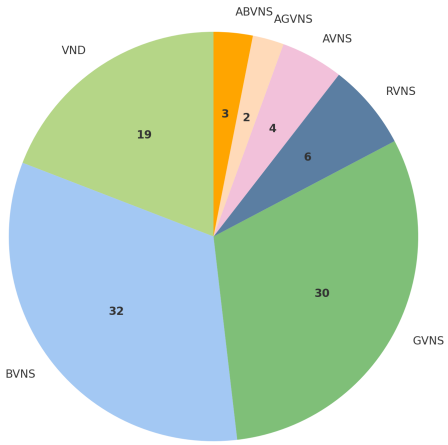


Figure 4. Distribution of publications per most common VNS versions.

The most challenging approach is the AVNS. Table 2 presents a chronological overview of the various studies on sustainable logistics that incorporate adaptability. The table categorizes the adaptability features based on their implementation in different phases of the VNS process or inside other optimization methods: in the shaking phase of the VNS, in the improvement phase of the VNS, in the selection of the next neighborhood, in the order in which neighborhoods are applied, in hybrid approaches deciding when VNS is applied, and in the search strategy (best improvement or first improvement). This table demonstrates that adaptability is most commonly utilized (marked with X) in the shaking and improvement phases of the VNS, with a particular emphasis on selecting the order in which neighborhoods are applied.

Table 2. Ways to include adaptability in AVNS.

Paper	Shake	Improve	Select	Order	Hybrid	Best/First
[27]	-	-	-	-	X	-
[28]	-	-	-	-	X	-
[19]	X	X	X	-	-	-
[14]	-	X	X	X	-	-
[20]	-	X	X	X	-	-
[29]	-	-	-	-	X	-
[31]	-	X	X	X	-	X
[23]	X	X	-	-	-	-
[24]	X	X	-	-	-	-
[15]	X	-	-	X	-	-
[21]	X	-	-	X	-	-
[25]	X	-	-	X	-	-
[22]	X	X	-	X	-	-
[16]	X	-	X	-	-	-
[30]	-	X	X	-	X	-
[17]	X	-	-	X	-	-
[18]	X	-	X	X	-	-
[26]	-	-	-	-	X	-

Specifically, in [19], a Memetic Algorithm (MA) incorporated AVNS as its local search heuristic to design a robust closed-loop global supply chain network for the medical device

industry under uncertainty. Another hybrid heuristic combining AVNS with Tabu Search (TS) was developed in [14] to solve the problem of routing and locating multiple charging stations for electric vehicles within time windows.

AVNS has also played a significant role in multiobjective optimization for sustainable supply chain management. In [27], an adaptive multiobjective VNS was used to optimize a two-echelon multi-vehicle location/routing problem with time windows for sustainable food supply chains. Extending this approach, ref. [28] integrated the strategic allocation of sustainable orders with a supply chain network under stochastic demand. Furthermore, ref. [29] conducted a comparative analysis of a multiobjective AVNS against other evolving algorithms to design a sustainable supply chain network integrated with vehicle routing.

Pollution location inventory routing problems have also been tackled with adaptive VNS variations. Ref. [31] applied an adaptive version of BVNS, and subsequent works [23,24] explored additional adaptations. A hybrid combining AVNS and ALNS was used in [15] to address a multi-level location/routing problem with environmental considerations.

In urban logistics, AVNS has been effectively applied to optimize waste collection and routing systems. Ref. [21] proposed an AVNS for sustainable urban recycling with heterogeneous electric vehicles, while ref. [25] extended this methodology with AGVNS to optimize electric truck routing for milk collection. For green manufacturing systems, ref. [22] developed a double-adaptive GVNS to address unmanned electric vehicle routing and scheduling. Similarly, ref. [16] utilized AVNS to solve a green flexible job shop problem, aiming to minimize both makespan and total energy consumption.

Beyond supply chains and urban logistics, AVNS has been hybridized with other methods for innovative applications. Ref. [30] combined AVNS with ABC to develop a customer-oriented solution for multi-task green scheduling with diverse time-of-use pricing in cloud manufacturing. Ref. [17] employed a self-adaptive VNS to design a sustainable freight transportation network incorporating cross-docks. In healthcare logistics, ref. [18] applied AVNS to a home healthcare routing problem with heterogeneous electric vehicles and synchronization. Additionally, [26] demonstrated the use of AVNS for vehicle routing problems with time windows and carbon emissions in logistics distribution. Finally, ref. [20] optimized the locations and routing for battery swap stations for capacitated electric vehicles using AVNS.

This diverse body of research illustrates the growing relevance of AVNS and its variants across diverse sustainable logistics applications, from supply chain design to waste collection and beyond. Its hybridization with other optimization methods has further enhanced its ability to address complex, real-world challenges while balancing economic, environmental, and operational objectives.

4.2. Hybridization Analysis

Figure 5 illustrates the frequency with which VNS is hybridized with various optimization techniques across the selected pool of academic papers. Appendix A contains the correspondence between acronyms and full names. Among these methods, Simulated Annealing (SA) stands out as the most commonly combined with VNS. This is likely due to the ease with which the SA cooling schedule can be incorporated into the VNS stopping criteria, allowing a smooth integration that enhances the optimization process.

VNS is also frequently employed as a local search operator in other evolutionary algorithms, such as the GA, evolutionary algorithm (EA), and MA. In these cases, VNS is often applied after mutation and crossover operations, refining the solutions generated by these algorithms and improving their overall effectiveness.

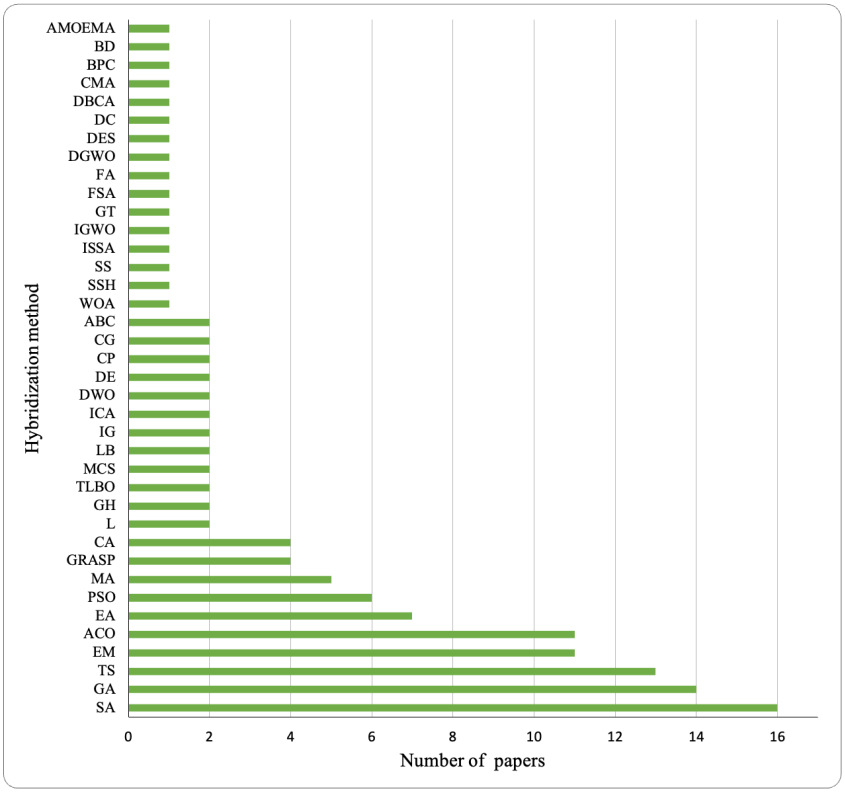


Figure 5. Methods combined with VNS to solve sustainable logistic problems.

The next in frequency is TS. In this hybridization, a tabu list is typically incorporated during the local search phase of VNS. The list is used to guide the selection of the next movement by preventing the algorithm from revisiting previously explored solutions, which promotes diversification and avoids local optima.

When it comes to matheuristics, which combine Exact Methods (EMs) with VNS, various strategies are possible depending on the specific problem being addressed. In some problems, an EM is used as a post-optimization technique to enhance the solutions obtained by VNS or to obtain an initial solution [51–53]. Other approaches involve using EMs to solve smaller parts of the problem inside the VNS [54,55]. In certain applications, such as scheduling/routing or location/routing problems, all these options are used to tackle distinct aspects of the problem, thus serving different roles within the overall algorithm [56].

A similar pattern can be observed for PSO and Ant Colony Optimization (ACO). These techniques can either be employed to act as the primary optimization methods with VNS, serving as a local search refinement [27,57–59], or address different stages of complex problems that are solved in conjunction, as seen in multiproblem scenarios [60].

In contrast, other algorithms appear to be combined with VNS far less frequently. Their hybridization occurs at a notably lower rate, suggesting that their integration has been less explored in the literature.

4.3. Multiobjective Analysis

Sustainable logistics inherently involves addressing multiple, often conflicting objectives, such as minimizing costs, reducing environmental impact, and ensuring social equity. These objectives reflect the three pillars of sustainability, which must be balanced to achieve effective and responsible logistics solutions. Multiobjective optimization methodologies are particularly relevant in this context, as they enable decision-makers to systematically explore and navigate trade-offs between these competing goals.

Of the 173 studies collected, 37 address multiobjective problems. In particular, studies focused on scheduling and network design are more likely to adopt multiobjective versions. These kinds of problems can be approached using various methods, each with its advantages and limitations. One of the simplest and most common techniques is to transform a multiple-objective problem into a single-objective one. This is typically accomplished through scalarization, where a weighted sum of the objectives is created, allowing for the adjustment of importance between the objectives by assigning different weights. By fine-tuning these weights, a decision-maker can explore different trade-offs between objectives, ultimately guiding the solution towards an optimal balance. Due to its simplicity, the number of studies using this kind of approach is among the highest in the context of this review [16,29,61–67].

Another approach is the ϵ-constraint method, which involves selecting one of the objectives as the primary goal to be optimized while treating the other objectives as constraints with varying upper bounds (right-hand side values). By systematically adjusting these constraints, multiple Pareto-optimal points can be generated, each representing a different compromise between competing objectives. This method provides a structured way to explore the Pareto front, offering a range of solutions that reflect different priorities.

Mathematically, the ϵ-constraint method can be expressed as:

$$\min f_1(x), \quad \text{subject to: } f_i(x) \leq \epsilon_i, \forall i \in \{2, \ldots, k\}, x \in X \tag{1}$$

where $f_1(x)$ is the primary objective and ϵ_i represents upper bounds for the secondary objectives $f_i(x)$. In the context of VNS for sustainable logistics, it is less frequently used [68,69]. This may be due to the high number of executions necessary to obtain the Pareto front changing the corresponding constraint, which makes it a laborious task.

A powerful technique for handling multiobjective optimization is the use of achievement scalarizing functions (ASFs). This method allows decision-makers to specify a target or aspiration level for each objective, and then the optimization process seeks to minimize the distance between the current solution and this desired achievement.

Mathematically, the ASF can be represented as:

$$\min S(x) = \max_{i \in \{1,\ldots,k\}} \left\{ w_i \cdot \frac{f_i(x) - z_i}{f_i^{\max} - f_i^{\min}} \right\}, x \in X \tag{2}$$

where z_i is the aspiration level for the i-th objective and w_i represents weights reflecting the decision-maker's preferences. The ASF generates a scalar value for each solution, representing how well it aligns with the defined aspiration levels, and the solution that minimizes this value is selected as optimal.

The flexibility of this method makes it useful for problems where decision-makers have specific performance targets for each objective. However, it is rarely applied in VNS-related studies for sustainable logistics [70].

In addition to approaches that transform the problem into a single-objective one, there is the option of addressing the problem as truly multiobjective from the outset. This direct approach allows the simultaneous optimization of all objectives without reducing them to a single aggregated function. In this context, evolutionary algorithms are commonly used to explore the solution space. These algorithms can generate an approximation of the Pareto set, which consists of non-dominated solutions representing the best possible trade-offs between competing objectives. This approach is used significantly more frequently than any other in our context [27,28,30,34,71–86]. This may be due to the fact that one of the key advantages of directly addressing a problem as multiobjective is that it provides a diverse set of solutions, giving decision-makers the flexibility to choose an option that

best fits their specific priorities or constraints, rather than being constrained by predefined weights or scalarized objectives. This approach is especially beneficial in complex problems where the objectives may conflict or be difficult to reconcile through simple weighting or constraint-based methods.

Another well-established method for directly addressing multiobjective problems is compromise programming, which aims to find solutions that are as close as possible to the ideal solution—a hypothetical point where all objectives are optimized simultaneously. In practice, such an ideal solution rarely exists, as objectives often conflict. However, compromise programming seeks to minimize the distance between feasible solutions and this ideal point by using distance metrics such as the L1 (Manhattan distance) or L2 (Euclidean distance) norms.

The mathematical formulation is:

$$L_p(x) = \left(\sum_{i=1}^{k} w_i \cdot \left| \frac{f_i(x) - f_i^*}{f_i^{\max} - f_i^{\min}} \right|^p \right)^{1/p} \tag{3}$$

where f_i^* represents the ideal value of objective i. The chosen norm (p) reflects the decision-maker's tolerance for trade-offs between objectives. In this method, the decision-maker specifies a preferred balance between objectives, and the algorithm then searches for solutions that are closest to this ideal according to the chosen norm. Therefore, this approach is particularly effective when the decision-maker has a clear understanding of the relative importance of each objective but still wants to explore solutions that lie near the ideal trade-off between them. Regrettably, this is not a common situation, as reflected by the number of approaches that use it in our context [87,88].

Finally, another technique for solving multiobjective problems is the lexicographic order method, which prioritizes the objectives according to their importance. In this approach, the objectives are ranked in hierarchical order, and the optimization process focuses first on the most important objective. Once an optimal solution is found for the highest-priority objective, the second most important objective is optimized, but only within the set of solutions that maintains optimality for the first. This process continues down the hierarchy, optimizing each subsequent objective without sacrificing the optimality of higher-priority ones.

Therefore, the lexicographic approach is expressed as a sequence of optimization problems:

$$\min f_1(x),\ x \in X, \tag{4}$$

$$\min f_2(x),\ x \in X \text{ such that } f_1(x) = f_1^*, \tag{5}$$

$$\ldots \tag{6}$$

This method is particularly useful when one or more objectives are clearly more critical than others and there is a need to maintain strict priority among them. However, one limitation of this method is that it can disregard potentially good trade-offs for lower-priority objectives, as it strictly adheres to the ranked order. This, along with the need to establish the critical order, makes it less popular in the pool of studies analyzed [69,89,90].

Figure 6 shows the distribution of the collected studies according to the multiobjective method. All these methods balance theoretical rigor with practical applicability. For example, scalarization techniques are straightforward and computationally efficient, making them ideal for preliminary studies or contexts with limited computational resources. On the other hand, approaches such as the lexicographic method and compromise programming offer structured ways to address problems with clear priority hierarchies or trade-offs, which are often encountered in sustainability-related decision-making scenarios.

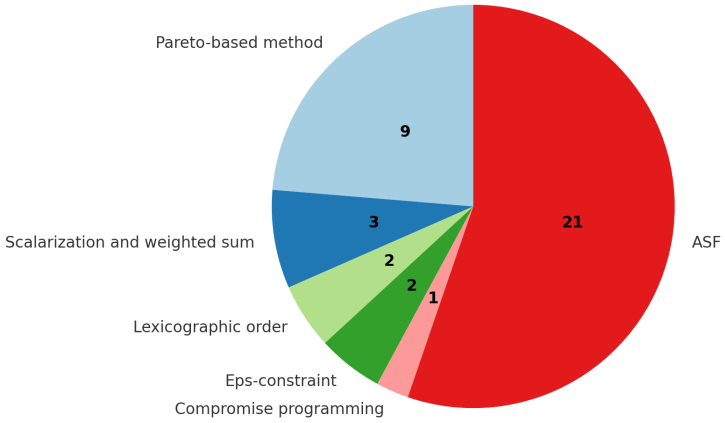


Figure 6. Distribution of studies according to the multiobjective approach.

4.4. Uncertainty and Dynamism Analysis

From the body of studies analyzed, only a limited number address uncertainty or dynamic factors in sustainable logistics problems, despite their critical impact on the effectiveness of the solution. Various sources of uncertainty are considered depending on the specific problem and the field of application. For instance, in [54], the authors tackle a location problem where vehicle travel costs and CO_2 emissions are uncertain, managed through a simulation-based optimization approach. Similarly, refs. [91,92] examine location/routing issues under uncertain conditions: Ref. [91] focuses on electric vehicle battery swap stations with fluctuating customer demand, applying two extended recourse policies to mitigate route failures. Meanwhile, ref. [92] employs a robust optimization framework to handle stochastic customer locations in a more generalized problem setting.

In network design, ref. [28] considers the uncertainty introduced by stochastic demand from retailers, applying a scenario-based stochastic model to address these variations. In routing, diverse uncertainties are managed in studies by [93–95]. Ref. [93] addresses pickup demand uncertainty through a two-stage method: initially estimating the pickup demands to create preliminary routes and then simulating these routes under real-time constraints and dynamically adjusting the unmet demands. In [94], service time uncertainty is tackled with robust optimization, while ref. [96] uses a simheuristic algorithm to manage unpredictable waste levels in a waste collection scenario. Additionally, ref. [95] considers energy consumption uncertainty in a similar context, employing robust optimization to create reliable routes.

Dynamic elements are even less frequently addressed. In [97], a routing problem for electric vehicles with dynamically arriving customers is managed through periodic re-optimization, transforming the dynamic situation into a sequence of static subproblems. Likewise, ref. [98] applies a dynamic programming algorithm to a scheduling problem influenced by dynamic disruptions, such as new order arrivals, variable raw material release times, and machine breakdowns.

Although uncertainty and dynamism are recognized as crucial factors in sustainable logistics, they remain underrepresented in optimization research where VNS is used. Studies that consider these elements rely on a range of advanced techniques, including robust and simulation-based optimization, scenario planning, and dynamic programming, each tailored to manage specific types of variability. However, the limited focus on these factors indicates a gap in the comprehensive integration of uncertainty and dynamism in sustainable logistics using VNS, particularly for complex real-world applications.

4.5. Sustainability Analysis

Sustainability in a logistic research publication is identified by including measures to evaluate and focusing on some of the aspects that are directly related to sustainability. As mentioned in the introduction, there are three aspects of sustainability: economic, environmental, and social sustainability. By considering optimization, the efficient management of resources is somehow taken into account in the final set of selected papers. Costs are part of models since this is the key aspect to guarantee the continuity of business and industries. This, jointly with the kinds of keywords used in the search, involves that the whole set of papers takes into account economic sustainability. Additionally, by considering the first set of keywords, environmental sustainability is also included in all the papers. However, social sustainability is less frequently considered in the research, and only a few papers take it into account.

The existing literature reveals that different studies adopt varying criteria depending on the specific problem, application, and context, making it challenging to establish a universal efficiency criterion applicable to all cases. Our methodology reflects this diversity by analyzing sustainability-related criteria individually, such as cost efficiency, environmental impacts, and social considerations, as these are tailored to the unique goals of each study.

In the following, we analyze the different criteria used to include the three aspects in the models and algorithms.

4.5.1. Economic Criteria

As previously mentioned, cost is a critical factor that is considered either directly or indirectly in all selected papers. Regardless of the specific optimization problem, cost minimization plays a central role in determining the efficiency and feasibility of the proposed solutions.

In the context of location problems, costs often encompass a variety of factors. These typically include the expenses associated with the installation of new facilities and the distances between demand points and their nearest service locations [54,99–101]. Minimizing these distances is crucial, as it directly impacts transportation costs, which are a major component of overall operational expenses in logistics networks. In some cases, other factors such as land acquisition and facility setup costs are also considered [71], especially when multiple locations are involved in the optimization process.

When it comes to vehicle routing problems, costs are generally reduced by minimizing travel time or total travel distance, as shorter routes result in lower fuel consumption and fewer operational expenses. In some papers, the cost model is further expanded to account for emissions and fuel costs, particularly in cases where sustainable logistics practices are a focus [35,57,102–104]. Additionally, penalties are sometimes incurred for specific operational inefficiencies, such as early or late arrivals (earliness or tardiness) and unscheduled stops or visits [105–107]. These penalties can significantly increase overall costs and are important to consider in routing scenarios where time windows or service guarantees are critical. The number of vehicles used is another potential cost factor, although it is less frequently considered [108,109]. However, when included, the size of the fleet directly impacts both capital expenditure and ongoing operational costs, such as driver wages and vehicle maintenance.

In scheduling problems, cost reduction is often linked to the minimization of the makespan—the total time required to complete all tasks or jobs. By reducing the makespan, companies can optimize resource allocation, increase throughput, and lower operational expenses such as labor and machine costs. In some cases, scheduling papers also factor in other costs related to delays or downtime, which can impact overall productivity [30,78].

Network design problems, on the other hand, tend to involve the most complex cost structures due to the multitude of elements involved in the optimization process. These problems typically integrate a wide range of costs, combining transportation expenses between different facilities, the costs associated with opening and operating facilities at different levels, and penalties related to tardiness in meeting delivery deadlines [34,62,63]. Furthermore, network design models often have to account for the fixed and variable costs of maintaining facilities over time, as well as any logistics costs associated with managing inventory, handling products, and maintaining service levels across the network [17,64,110].

In many cases, these cost components are interrelated, and the trade-offs between them must be carefully considered in the optimization process. For example, opening additional facilities may reduce transportation costs by shortening delivery routes, but it also increases fixed facility costs. As a result, papers addressing network design often present highly sophisticated cost models that balance these competing factors to find the most cost-effective solution for complex supply chain and logistics problems.

4.5.2. Environmental Criteria

In the context of the use of VNS for sustainable logistics, we have identified several key environmental aspects that are commonly addressed in research. We have further categorized each paper based on these specific aspects. To facilitate this, we considered 11 distinct fields:

- Electric vehicles: This category includes papers that explore the use of electric vehicles (EVs), which are pivotal in reducing the environmental impact of logistics by minimizing reliance on fossil fuels.
- Emissions: Papers in this group focus on strategies to minimize emissions, such as carbon dioxide, nitrogen oxides, and particulate matter, from transportation and logistics operations, highlighting the importance of cleaner and greener practices.
- Waste collection: This category encompasses studies dedicated to optimizing waste collection systems, improving efficiency while ensuring sustainable waste management practices.
- Energy consumption: Papers classified here address the reduction in energy consumption within logistics operations. Some of these studies involve mixed fleets that combine traditional and alternative energy sources, with a focus on improving overall energy efficiency.
- Drones: This field includes research that explores the use of electric drones for logistics, which offers the potential for lower emissions and greater efficiency in last-mile delivery, particularly in urban or remote areas.
- Reverse logistics: Papers in this category focus on reverse logistics processes, which involve the return of goods from consumers to producers, and emphasize sustainable practices such as recycling and reusing products.
- Closed-loop logistics: This category includes studies that look into closed-loop logistics systems, which are designed to ensure products are reused or recycled, minimizing waste and reducing the need for raw materials.
- Clean energies: This field encompasses papers exploring the use of clean energy sources such as wind farms, biomass energy, and photovoltaic (solar) energy within logistics, aiming to reduce the environmental footprint of operations.
- Sustainable Tourism: Studies in this category focus on the intersection of logistics and sustainable tourism, addressing how transportation and logistics systems can support environmentally responsible travel practices.
- Noise pollution: This group includes papers that address the issue of noise pollution, which is an often-overlooked aspect of sustainability in logistics, focusing on strategies to reduce noise emissions from transportation vehicles and operations.

- Wastewater collection: Finally, papers related to wastewater collection explore logistics systems that are designed to manage and transport wastewater in a sustainable manner, minimizing environmental impact and optimizing infrastructure.

By organizing the papers into these 11 categories (see Table A1), we provide a clearer understanding of how environmental criteria are integrated into various logistics problems using the VNS and highlight the diverse ways in which environmental concerns are being addressed in the field. Figure 7 shows the distributions of papers according to these categories. Among these various fields, the use of electric vehicles and the reduction in carbon emissions are the most frequently considered in the literature. This reflects the growing global emphasis on decarbonizing the transportation sector and transitioning toward greener logistics practices.

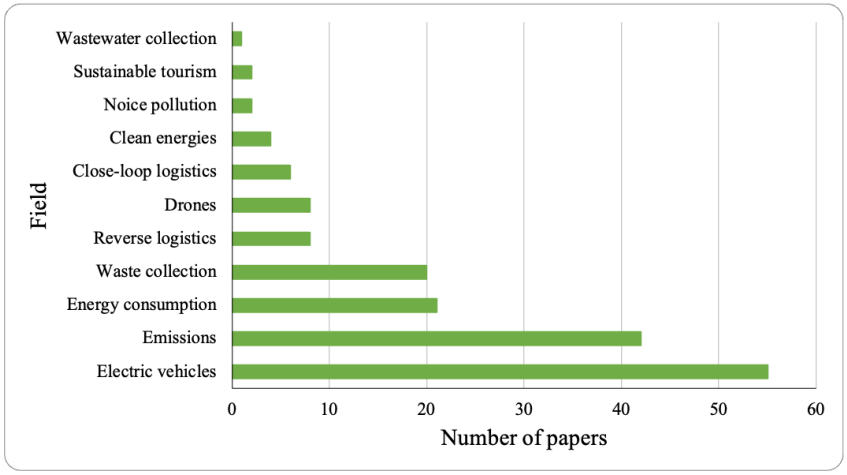


Figure 7. Number of publications per sustainability field.

4.5.3. Social Criteria

From the set of selected papers, only a limited number directly address social aspects within the scope of optimization problems. However, those that do tend to focus on important human-centered criteria, particularly when dealing with scheduling problems. For instance, one factor is the minimization of repetitive occupational actions, which aims to reduce worker fatigue and the risk of long-term injuries associated with repetitive tasks [82]. Another social criterion that is incorporated is the level of worker satisfaction, which reflects the importance of employee well-being in operational decision making and seeks to balance productivity with a positive and sustainable work environment.

In the realm of network design and distribution optimization, several social aspects come into play. One notable criterion is the creation of fixed job opportunities, which highlights the potential for new facilities and infrastructure to provide stable employment in the surrounding community [64,84]. This is often linked to broader goals of fostering regional economic development, ensuring that the expansion of logistics and supply chain networks has a positive socio-economic impact. Moreover, worker safety is an important concern, particularly during both the establishment of new facilities and the initial stages of operation [64]. Research in this area often emphasizes the need to design processes and facilities that minimize hazards and promote a safe working environment.

In the context of vehicle routing problems, route balance in terms of time or distance can be considered as a social criterion, since drivers feel a fair distribution of work [38]. Another critical social consideration is the reduction in accident risks [35]. This is particularly relevant in urban logistics and last-mile delivery, where the higher density of traffic increases the likelihood of accidents. By optimizing routes not only for efficiency but also for safety, these studies aim to minimize the exposure of drivers and other road users to

potentially dangerous situations. This approach highlights the importance of integrating social and safety considerations into operational planning, ensuring that logistic systems do not compromise the well-being of those involved or impacted by processes.

Overall, while the number of papers that address these social dimensions is relatively small compared to environmental and economic factors, the integration of social criteria, such as worker well-being, safety, job creation, and accident risk reduction, reflects an important shift towards more holistic and sustainable decision making in logistics and supply chain management.

5. Research Trends and Gaps

The analysis of the current literature on the use of VNS in sustainable logistics reveals several trends and gaps that point to future opportunities for research in this area. Some trends are summarized in the following points.

- Growth in publications. As illustrated in Figure 1, there has been a notable rise in the number of publications on VNS in sustainable logistics since 2019. This trend reflects the increasing awareness and recognition of optimization methods like VNS in addressing complex and pressing challenges in logistics systems while promoting sustainability. The rapid growth in interest highlights the broadening application of VNS techniques in response to the global demand for more sustainable and efficient logistics practices.
- Dominance of operational research and computer science journals. The majority of studies in this field are published in journals related to operations research, computer science, and engineering. Journals such as *Computers & Operations Research* and *Computers & Industrial Engineering* are particularly prominent, as depicted in Figure 2.
- Focus on routing and scheduling. The optimization problems most frequently addressed in the reviewed studies are routing and scheduling. As shown in Figure 3, the majority of papers using VNS target these two areas, underlining their centrality in sustainable logistics. These problems are essential for reducing transportation costs, improving efficiency, and minimizing environmental impacts, all of which are core elements of sustainable logistics practices.
- Multiobjective optimization. An expanding body of research focuses on multiobjective problems where VNS is applied to simultaneously optimize conflicting objectives. These studies are vital for developing logistics systems that not only minimize costs but also integrate sustainability considerations such as emissions reduction, energy efficiency, and resource conservation. Multiobjective approaches remain highly relevant as they enable decision-makers to balance economic, environmental, and social goals in logistics systems.
- Hybridization with other methods. A significant trend is the hybridization of VNS with other optimization techniques. As indicated in Figure 5, methods such as SA, TS, and GA are commonly combined with VNS to improve solution quality. This hybridization enhances flexibility and facilitates the exploration of complex optimization problems.
- Prevalence of VNS variants. GVNS and BVNS remain the most widely used VNS variants, with a growing interest in the use of AVNS over the past few years.

Regarding research gaps and future research directions, we summarize the following points:

- Lack of focus on uncertainty and dynamism. While uncertainty and dynamism are critical factors in sustainable logistics, few studies incorporate these elements into VNS-based models. Uncertainty in demand, travel times, and environmental conditions, as well as the dynamic nature of logistics networks, can substantially

impact optimization algorithms. Future research could explore robust optimization techniques and dynamic adaptation mechanisms to make VNS more applicable to real-world logistics challenges.

- Limited exploration of social sustainability. Although economic and environmental sustainability are often addressed in VNS-based logistics optimization, the social dimension remains underrepresented. Social factors, such as worker well-being, job creation, and safety, require more attention in the literature. Including these social metrics in optimization models is essential to ensuring logistics practices are socially responsible and equitable.
- Innovation in hybridization techniques. While VNS has been successfully combined with various methods, further innovation in hybridization strategies is needed. Incorporating emerging technologies such as machine learning and reinforcement learning into VNS frameworks has received limited attention but holds significant potential for advancing sustainable logistics.
- VNS variants. The proliferation of VNS variants and terminologies necessitates a more structured classification. Additionally, some researchers label their methods as VNS when applying neighborhood-based searches, even when they primarily use local search strategies. A systematic clarification of these methodologies would enhance understanding and consistency in the field.
- Broader integration of sustainability metrics. While environmental sustainability remains a central focus, optimization models often lack comprehensive metrics. Factors such as resource efficiency, waste minimization, and community impact should be incorporated into future models to provide holistic solutions.
- Need for comprehensive benchmarks and standardization. A major challenge in applying VNS to sustainable logistics is the absence of standardized benchmarks and performance metrics. Standardizing problem definitions, datasets, and evaluation metrics would improve the comparability of results across studies and facilitate a clearer understanding of the strengths and limitations of VNS approaches.
- Emerging areas of application. New application domains for VNS in sustainable logistics are emerging, including renewable energy logistics, last-mile delivery using drones, and sustainable tourism optimization. Exploring and adapting VNS techniques to these novel challenges will expand their applicability and foster innovation in logistics research.

6. Discussion

VNS offers several advantages when addressing sustainable logistics problems. Its metaheuristic nature allows it to tackle large-scale, combinatorial optimization problems efficiently. The systematic exploration of neighborhood structures ensures a balance between exploration and exploitation, making VNS particularly suitable for problems with complex, multimodal solution landscapes. Furthermore, VNS is flexible and can be hybridized with other optimization methods, enhancing its applicability to multiobjective problems and dynamic scenarios. However, VNS is not without limitations. One drawback is its dependency on the definition and size of neighborhood structures, which can significantly influence the algorithm's performance. Poorly chosen neighborhoods may lead to suboptimal solutions or increased computational time. Another limitation is that VNS is inherently heuristic, meaning that it does not guarantee finding the global optimum. Moreover, implementing VNS for real-world logistics problems requires domain-specific knowledge to properly adapt the algorithm, which can pose challenges for practitioners without sufficient expertise.

When using VNS, practitioners must carefully define problem-specific parameters, such as neighborhood structures and shaking mechanisms, to achieve desired results. The method's reliance on computational power can also become a bottleneck for very large-scale problems or scenarios involving real-time decision-making. Recommendations for improving its application include integrating VNS with advanced machine learning techniques to enhance parameter tuning and combining it with robust optimization frameworks to address uncertainty in logistics data. While VNS is a powerful optimization tool, alternative methods such as GA, TS, and PSO are also widely used in sustainable logistics. GAs, for instance, offer strong exploratory capabilities due to their population-based approach, but they may struggle with convergence speed. TS provides effective intensification strategies but can become trapped in local optima without proper diversification. PSO, on the other hand, is efficient for continuous problems but may require additional adaptation for discrete or combinatorial problems. Compared to these methods, VNS stands out for its structured search and adaptability, although the choice of the method should ultimately depend on the problem characteristics and computational resources available.

One noteworthy observation from our analysis is the prevalent approach to formulating optimization problems where the objective is often defined as the minimization of a composite function. Specifically, many studies focus on reducing a sum of diverse cost components, and in certain cases, this objective incorporates a linear combination of multiple cost factors and sustainability metrics to evaluate the solution's overall impact. In some studies, an economic valuation of some effect contrary to sustainability, such as emissions or other collateral effects, is used. Such optimization problems could, and in some cases should, be treated as multiobjective problems, where the optimization of a linear combination of objectives being only one of the possible alternatives to address it. There are not many articles in the literature on the application of VNS alone to address multiobjective problems, both in sustainable logistics and in other areas, but the use of hybrids of two or more metaheuristics is more frequent, with some VNS versions being one of them.

A key issue in the design and application of VNS is the choice of the series of neighborhood structures to use and also the order in which they are applied. Originally, it was recommended to use them by size or in order of complexity, from smallest to largest size or from least to most complex [7]. Different strategies have also been studied to change the neighborhood structure different from the original sequential change step, such as the cyclic, pipe, and skewed change step ([11]).

However, very few authors of papers justify the choice of the neighborhood structures to include in the VNS implementation they apply. In general, for any optimization problem, a large number of different structures can be devised, but only a few are chosen. The selected structures must be those that contribute significantly to the good performance of the procedure, discarding those that do not provide an additional contribution to those already considered. This must be accomplished through an experimental study on a sufficiently significant bank of instances using statistical techniques such as Factor Analysis or Principal Component Analysis. For example, some researchers use, say, eight or even more structures in their proposal. We should ask ourselves if similar results could be obtained for a subset of these structures. The simplicity and effectiveness that are at the heart of the original VNS proposal [8] have led to the formulation of the "Less is More" approach [111].

Unfortunately, this experimentation is not usually conducted due to the high computational costs of an exhaustive analysis and because it generally contributes little to what the experts' or authors' intuitions dictate. This same methodology should also be applied when considering hybrids or incorporating elements of other metaheuristics, as is frequently the

case with tabu lists (TSs) or acceptance functions (SAs). When proposing a hybrid method, it must be proven that it provides advantages over each of them separately.

These techniques should also be applied to decide the order in which the different environment structures are applied within the VNS, either for agitation or enhancement or even both. It should also be used for the selection of the best improvement versus the first improvement strategy [32].

A step further along this line involves the proposals that try to incorporate AI procedures so that the algorithm itself automatically keeps the structures and movements that are relevant, discarding those that are superfluous. In this sense, adaptive systems or versions have been proposed, in particular the methods known as AVNS, which generally use a weighting system for the different structures or movements based on the number and intensity of the improvements that are achieved by applying each of the structures considered.

7. Conclusions

The analysis of recent trends in the literature on VNS for sustainable logistics highlights key findings and future directions. Since 2019, there has been a significant increase in publications on VNS, demonstrating its potential to tackle complex logistics challenges and promote sustainability. Most studies focus on routing and scheduling problems, which are critical for reducing costs and environmental impacts. The most frequently used VNS variants are GVNS and BVNS. Additionally, the growing interest in multiobjective optimization reflects the increasing need to achieve a balance between economic, environmental, and social goals in logistics systems. The hybridization of VNS with techniques such as SA, TS, and GA has enhanced both flexibility and solution quality for complex logistics problems.

However, significant gaps remain. One key gap is the underrepresentation of uncertainty and dynamism in VNS models, despite their relevance to real-world logistics networks with fluctuating demand and variable travel times. Future research should explore robust optimization methods and dynamic adaptation mechanisms to improve the practical applicability of VNS.

Another critical gap is the limited focus on social sustainability, in contrast to the more frequently addressed economic and environmental dimensions. Aspects such as worker well-being, safety, and job creation must be integrated into models to promote socially responsible logistics practices. Moreover, there is significant potential to innovate by combining VNS with emerging technologies, such as machine learning and reinforcement learning, which could help address the complexities of evolving logistics challenges.

The lack of standardized benchmarks and performance metrics for VNS in sustainable logistics is another challenge. Establishing common standards would facilitate more meaningful comparisons across studies and support the identification of strengths and weaknesses in VNS applications. Furthermore, while environmental sustainability is frequently addressed, broader integration of metrics such as resource efficiency and waste reduction is essential for achieving comprehensive optimization.

New application areas, including renewable energy logistics, last-mile delivery using drones, and sustainable tourism, offer exciting opportunities for advancing VNS research. Adapting VNS methods to address these novel challenges could pave the way for innovation and practical advancements.

This study also reveals areas for improvement and caution when implementing VNS. A critical insight is the prevalent focus on minimizing a composite function that combines cost factors and sustainability metrics. While this approach provides a straightforward framework, it often oversimplifies the interrelations and trade-offs inherent in sustainability-focused logistics problems. Treating such problems as genuinely multiobjective rather than

relying solely on weighted linear combinations could yield richer solutions. Furthermore, the literature indicates that hybrid approaches involving VNS are more common than standalone applications for multiobjective problems, showcasing the importance of combining VNS with complementary methods for enhanced performance.

A recurring issue is the lack of systematic justification for key algorithmic choices in VNS implementations, such as neighborhood structures, their order of application, and the strategy for improvement selection. While expert intuition often guides these decisions, rigorous experimental validation is necessary to ensure the efficiency and effectiveness of the selected structures.

Emerging trends, such as the use of adaptive versions, offer promising avenues to enhance VNS. By incorporating AI techniques, these methods dynamically adjust the relevance of neighborhood structures based on performance, paving the way for more robust and automated optimization. However, this adaptability must also be backed by thorough experimentation to validate its impact on solution quality and computational efficiency.

In conclusion, while VNS remains a powerful and versatile tool for sustainable logistics, its success depends on carefully considered methodological choices, robust validation, and adaptation to the specific problem context. Addressing these aspects can significantly enhance the applicability and effectiveness of VNS, ensuring it remains a cornerstone for sustainable logistics optimization.

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Abbreviations

The following abbreviations are used in this manuscript:

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ASF	Achievement Scalarizing Functions
ABVNS	Adaptive Basic Variable Neighborhood Search
AGVNS	Adaptive General Variable Neighborhood Search
ALNS	Adaptive Large Neighborhood Search
AVNS	Adaptive Variable Neighborhood Search
BD	Benders Decomposition
BPC	Branch-and-Price-and-Cut
BVNS	Basic Variable Neighborhood Search
CA	Cellular Automata
CG	Column Generation
CMA	Cellular Memetic Algorithm
CP	Compromise Programming
DBCA	Density-Based Clustering Algorithm
DC	Divide and Conquer
DE	Differential Evolution
DES	Discrete Event Simulation
DGWO	Discrete Genetic-Grey Wolf Optimization Algorithm

DWO	Discrete Whale Optimization
EA	evolutionary algorithms
EM	Exact Method
EMA	Electro-Magnetism Algorithm
FA	Firefly Algorithm
FSA	Fish Swarm Algorithm
GA	Genetic Algorithm
GH	Greedy heuristic
GRASP	Greedy randomized adaptive search procedure
GT	Game Theory
GVNS	General Variable Neighborhood Search
ICA	Imperialist Competitive Algorithm
IG	Iterated Greedy
IGWO	Improved Gray Wolf Optimization Algorithm
ISSA	Improved Sparrow Search Algorithm
L	Learning
LB	Local Branching
MA	Memetic Algorithm
MCS	Monte Carlo Simulation
MO	multiobjective
PSO	Particle Swarm Optimization
RVNS	Reduced Variable Neighborhood Search
SA	Simulated Annealing
SLP	Sustainable Logistic Problem
SLR	Systematic Literature Review
SS	Scatter Search
SSH	Space-Saving Heuristic
SVNS	Skewed Variable Neighborhood Search
TLBO	Teaching-Learning-Based Optimization
TS	Tabu Search
VNS	Variable Neighborhood Search
VND	Variable Neighborhood Descent
WOA	Whale Optimization Algorithm

Appendix A. Summary of Papers Reviewed

Table A1 presents a summary of all the papers selected for the present review. Each column corresponds to the reference, the decision problem addressed, the field, if it deals with uncertainty (U), if it deals with dynamism (D), if it includes social sustainability criteria (SS), the objective function(s) considered, if it addresses a multiobjective problem (MO), the VNS variant used, and the method used for hybridization (if any). Note that a * in the objective column means that emissions are considered as part of the cost.

Table A1. Studies on logistics optimization using VNS.

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[99]	Location/Scheduling	Electric vehicles				Min number of charging points		GVNS	
[112]	Location	Electric vehicles				Max profit		GVNS	GHs
[71]	Location	Electric vehicles				Min cost/Max coverage	✓	Sequential VND	SS
[101]	Location	Electric vehicles				Min distance		GVNS	
[100]	Location	Reversed logistics				Min travel cost		BVNS	
[54]	Location	Emissions	✓			Min travel cost		BVNS	EM, MCS
[27]	Location/Routing	Emissions				Min cost/Min environmental impact	✓	AGVNS	PSO
[14]	Location/Routing	Electric vehicles				Min cost		AVNS	TS
[20]	Location/Routing	Electric vehicles				Min cost		AVNS	
[31]	Location/Routing/Inventory	Emissions				Min cost *		ABVNS	
[91]	Location/Routing	Electric vehicles	✓			Min cost		BVNS	PSO
[23]	Location/Routing/Inventory	Emissions				Min cost *		AVNS	
[24]	Location/Routing/Inventory	Emissions				Min cost *		AGVNS	
[113]	Location/Routing	Electric vehicles				Min cost		BVNS	
[36]	Location/Routing	Electric vehicles				Min cost		SGVNS	
[114]	Location/Routing	Clean energies				Min cost		BVNS	TS
[92]	Location/Routing	Emissions	✓			Min cost *		RVNS	ICA
[15]	Location/Routing	Emissions				Min cost *		AGVNS	ALNS
[60]	Location/Routing	Electric vehicles				Min cost		VND	ACO
[115]	Location/Routing	Electric vehicles				Min cost		BVNS	
[116]	Location/Routing	Electric vehicles				Min cost		GVNS	
[117]	Location/Routing/Inventory	Emissions				Min cost		BVNS, GVNS with cyclicVND, pipeVND	
[118]	Location/Routing	Waste collection				Min cost		BVNS	MA
[119]	Location/Routing	Electric vehicles				Min cost		BVNS	
[120]	Location/Routing	Electric vehicles				Min time		GVNS	
[121]	Location/Routing	Clean energies				Min cost		GVNS	GA
[122]	Location/Routing	Clean energies				Min cost		GVNS	
[123]	Location/Routing	Waste collection				Min cost		BVNS	
[124]	Location/Routing	Electric vehicles				Min distance		BVNS	GA
[125]	Location/Routing	Waste collection				Min cost		VND	

Table A1. *Cont.*

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[87]	Scheduling	Wind farm				Min cost/Min completion period	✓	BVNS	CP, SA
[126]	Scheduling	Emissions				Min CO_2 emission		VND/RVNS	
[72]	Scheduling	Noise pollution				Min makespan/Min noise pollution	✓	BVNS	CA
[127]	Scheduling	Energy consumption				Min cost		RVNS	DWO
[89]	Scheduling	Cross-docking				Min energy consumption/Min cost	✓	BVNS	SA, TS
[128]	Scheduling	Energy consumption				Min cost		BVNS	DWO
[73]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	VND	MAs
[61]	Scheduling	Emissions/Noise pollution				Min completion time/Min energy consumption	✓	BVNS	IGWO, PSO
[129]	Scheduling	Energy consumption				Max net revenue		GVNS	
[74]	Scheduling	Energy consumption				Min makespan/Min worker cost/Min green indicator	✓	VND	EA
[130]	Scheduling	Energy consumption				Min cost		BVNS	DGWO
[68]	Scheduling	Energy consumption				Min energy consumption/Min surplus stocks	✓	RVNS	TLBO
[131]	Scheduling	Emissions				Min carbon emissions		RVNS	
[98]	Scheduling	Energy consumption		✓		Min energy consumption		BVNS	
[75]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	VND	TLBO
[76]	Scheduling	Energy consumption				Min makespan/Min energy cost	✓	VND	EA
[132]	Scheduling	Electric vehicles				Min cost		GVNS	BD
[133]	Scheduling	Clean energy				Min electricity consumption		BVNS	TS
[77]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	VND	CMA
[78]	Scheduling	Energy consumption				Min makespan/Min equipment load/Min energy consumption/Min delay time/Min processing quality	✓	VND	EA
[134]	Scheduling	Energy consumption				Min cost		VND	ISSA
[16]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	AVNS	
[79]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	VND	
[30]	Scheduling	Energy consumption				Min energy consumption/Min earliness and tardiness	✓	AVNS	ABC
[102]	Scheduling	Energy consumption				Min energy consumption		GVNS	GA, EM
[80]	Scheduling	Energy consumption				Min makespan/Min energy consumption	✓	VND	GA
[81]	Scheduling	Energy consumption				Min tardiness/Min energy cost/Min carbon trading cost	✓	GVNS	EA, L
[82]	Scheduling	Energy consumption			✓	Min makespan/Min maximum occupational repetitive action index/Max minimum level of satisfaction of all workers/Min energy consumption	✓	BVNS	GA, L

Table A1. *Cont.*

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[83]	Scheduling/Routing	Emissions				Min tardiness/Min energy consumption	✓	BVNS	EA
[135]	Scheduling/Routing	Emissions				Min cost *		VND	GA, SA
[136]	Scheduling/Routing	Electric vehicles				Min travel time		BVNS and VND	EA
[137]	Scheduling/Routing	Emissions				Max profit		BVNS	
[22]	Scheduling/Routing	Electric vehicles				Min travel time		AGVNS	
[138]	Scheduling/Routing	Electric vehicles			✓	Min cost		BVNS	BPC, CG
[52]	Scheduling/Routing	Wind farm				Min cost		BVNS	EM
[139]	Scheduling/Routing	Electric vehicles				Min cost		BVNS	
[18]	Scheduling/Routing	Electric vehicles				Min cost		AVNS	GRASP
[34]	Network design	Reversed logistics				Min cost/Min tardiness/Min pollution	✓	Parallel BVNS with SVNS	
[84]	Network design	Closed-loop logistics			✓	Min cost/Min environmental impact/Max job opportunities	✓	RVNS	ICA
[62]	Network design	Reversed logistics				Min cost/Min tardiness	✓	BVNS	
[28]	Network design (and order allocation)	Emissions	✓			Min cost/Min environmental impact	✓	ABVNS	Adaptive MO-EMA
[19]	Network design	Closed-loop logistics				Max total net present value		ABVNS	GA
[29]	Network design	Emissions			✓	Min cost/Min environmental impact and social impacts	✓	ABVNS	PSO, EMA, ABC, GA
[63]	Network design	Reversed logistics				Min cost/Min tardiness	✓	RVNS	
[64]	Production/Distribution/ Inventory/Allocation/Location	Emissions			✓	Min cost/Max social factors	✓	BVNS	ACO, FSA, FA
[140]	Network design	Emissions				Max profit		GVNS	GT
[110]	Network design	Emissions				Min cost *		GVNS	SA
[88]	Network design	Closed-loop logistics				Min cost/Min carbon emissions	✓	BVNS	CP
[65]	Network design	Closed-loop logistics				Min cost/Max crop yield and phosphorus use	✓	BVNS	WOA
[17]	Network design	Emissions				Min cost *		Two-Level AVNS	
[66]	Network design	Wastewater collection				Min cost/Min energy comsuption	✓	BVNS	DC
[141]	Network design	Emissions				Min cost/Min emissions		BVNS	GA
[85]	Network design	Electric vehicles				Min avg travel time/Min number of stations	✓	MO-VNS	

Table A1. *Cont.*

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[142]	Routing	Waste Collection				Min time		VND	
[143]	Routing	Waste Collection				Min time/distance		VND	TS
[144]	Routing	Waste Collection				Min time		BVNS	SA
[145]	Routing	Waste Collection				Min cost		BVNS	EM
[146]	Routing	Electric vehicles				Min distance		BVNS	TS,SA
[147]	Routing	Waste Collection				Min cost		BVNS	SA
[93]	Routing	Closed-loop logistics	✓			Min cost		GVNS	
[148]	Routing	Reversed logistics				Min distance		GVNS	
[40]	Routing	Electric vehicles				Min time		VNS Branching	LB
[149]	Routing	Electric vehicles				Min distance		VND	
[51]	Routing	Emissions				Min cost		BVNS	EM
[57]	Routing	Emissions				Min cost *		VND	ACO
[96]	Routing	Waste Collection	✓			Min cost		BVNS	MCS
[150]	Routing	Electric vehicles				Min time		VNS Branching	LB
[151]	Routing	Emissions				Min fuel consumption		GVNS	
[94]	Routing	Waste Collection	✓			Min time		BVNS	
[152]	Routing	Emissions				Min carbon emissions		GVNS	
[97]	Routing	Electric vehicles		✓		Min distance		GVNS	
[153]	Routing	Electric vehicles				Min cost		GVNS	
[154]	Routing	Electric vehicles				Min distance		GVNS	
[86]	Routing	Emissions				Min emissions/Min delay	✓	GVNS	
[35]	Routing	Emissions			✓	Min traveling time + traveling distance + environmental cost + social cost		SVNS	
[155]	Routing	Emissions				Min cost		GVNS	EA
[156]	Routing	Waste collection			✓	Max social welfare		BVNS	TS
[70]	Routing	Waste collection				Min total and maximum distance	✓	GVNS	IG
[157]	Routing	Emissions				Min cost		BVNS	PSO
[158]	Routing	Electric vehicles				Min cost		GVNS	SSH
[159]	Routing	Electric vehicles				Min cost		IVNS	
[160]	Routing	Electric vehicles				Min energy compsuption		GVNS	
[161]	Routing	Emissions				Min distance		GVNS	TS
[162]	Routing	Emissions				Min cost		VNS	GA,TS
[163]	Routing	Emissions				Min distance		VND	ACO
[164]	Routing	Waste collection				Min cost		GVNS	
[165]	Routing	Electric vehicles				Min cost		GVNS	
[166]	Routing	Electric vehicles				Min cost		BVNS	TS
[105]	Routing	Electric vehicles				Min time + TW deviation + unscheduled visits + overtime		VND	

Table A1. *Cont.*

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[167]	Routing	Electric vehicles				Min cost		GVNS	
[90]	Routing	Emissions				Max number of customers served by PDs and ODs/Max usage rate of professional vehicles/Min unfairness of PD routes/Min cost of operating cost ODs	✓	Memory-based GVNS	
[168]	Routing	Emissions				Min cost		VND	ACO
[169]	Routing	Waste collection				Min cost		BVNS	ACO
[21]	Routing	Waste collection				Min cost		AVNS	
[69]	Routing	Sustainable tourism				Max profit/Min cost/Min emissions	✓	GVNS	
[43]	Routing	Drones				Min cost		ILS	
[170]	Routing	Electric vehicles				Min distance		BVNS	TS
[55]	Routing	Electric vehicles				Min cost		BVNS	EM
[171]	Routing	Electric vehicles and drones				Min energy consumption		VND	ACO
[172]	Routing	Electric vehicles				Min distance		RVNS	
[173]	Routing	Electric vehicles				Min distance		GVNS	
[174]	Routing	Waste Collection				Min cost		GVNS	SA
[104]	Routing	Emissions				Min cost *		RVNS	
[37]	Routing	Emissions				Min cost		GVNS	
[38]	Routing	Emissions			✓	Min cost		RVNS	SA
[175]	Routing	Sustainable tourism			✓	Max number of tourists		BVNS	DE
[176]	Routing	Drones				Min energy consumption		VND	GRASP
[67]	Routing	Drones				Min completion time/Min costs/Min truck emission/Min penalty	✓	GVNS	SA
[177]	Routing	Drones				Min final arrival time at the depot		RVNS	
[178]	Routing	Emissions				Min cost		GVNS	
[179]	Routing	Electric vehicles				Min cost		GVNS	DBCA
[108]	Routing	Electric vehicles				Min energy consumption + number of vehicles		GVNS	SA
[56]	Routing	Electric vehicles				Min cost		BVNS	EM
[106]	Routing	Electric vehicles				Min travel time + penalty for missing time windows		GVNS	
[180]	Routing	Electric vehicles				Min cost + number of vehicles		BVNS	SA
[25]	Routing	Electric vechiles				Min cost		AGVNS	
[109]	Routing	Electric vehicles				Min energy consumption + number of vehicles		GVNS	BSO, ACO
[181]	Routing	Emissions				Min emissions/Min vehicle cost/Min fuel consumption/Min delay	✓	VND	PSO

Table A1. *Cont.*

Ref.	Decision Problem	Field	U	D	SS	Objective	MO	VNS Variant	Hybrid
[182]	Routing	Emissions				Min carbon emissions		GVNS	GA
[183]	Routing	Emissions				Min carbon emissions		BVNS	
[26]	Routing	Waste collection				Min cost		AVNS	SA
[184]	Routing	Electric vehicles and drones				Min final completition time		GVNS	
[95]	Routing	Electric vehicles	✓			Min recharging		GVNS	TS, SA, CG
[53]	Routing	Electric vehicles				Min cost		GVNS	EM
[185]	Routing	Electric vehicles				Min maximum distance traveled		VND	GA, GH
[53]	Routing	Electric vehicles				Min cost		GVNS	EM
[186]	Routing	Electric vehicles				Min cost		GVNS	
[107]	Routing	Emissions				Min cost *		Sequential VND	GA
[187]	Routing	Electric vehicles				Min cost		GVNS	ACO
[103]	Routing	Drones				Min cost *		Randomized VNS	
[184]	Routing	Drones				Min completion time		BVNS	
[188]	Routing	Waste collection				Min cost		GVNS	GA, SA
[58]	Routing	Emissions				Min cost		GVNS	ACO
[59]	Routing	Waste collection				Min cost		VND	ACO
[189]	Routing/Packing	Energy consumption				Min cost		BVNS	GRASP
[190]	Layout	Wind farm				Min annual production cost per unit power		BVNS	GRASP
[191]	Inventory	Reverse logistics				Min cost		BVNS	TS, DES
[192]	Lot sizing	Closed-loop logistics				Min cost		GVNS	
[193]	Lot sizing	Reverse logistics				Min cost		GVNS variants	
[194]	Lot sizing	Reverse logistics				Min cost		VND	
[195]	Layout	Wind farm				Min transportation cost		BVNS	EM
[196]	Layout	Wind farm				Max power production—wakes and foundation costs		BVNS	

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