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A survey of adaptive large neighborhood search algorithms and applications

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ABSTRACT

This article provides a survey on the highly popular metaheuristic framework, the adaptive large neighborhood search (ALNS). The basic concepts of ALNS are discussed in this paper. Based on a simple taxonomy, the analysis of publication intensity, application areas, and the variant of ALNS features are executed on 252 scientific publications to synthesize the state-of-the-art of ALNS research. Finally, some discussions on the future research of ALNS are provided.

1. Introduction

In the attempts to find global optimum solutions for optimization problems, studies in the last 15 years have shown us an increasing number of proposals on Adaptive Large Neighborhood Search (ALNS). ALNS is a relatively new metaheuristic which was first introduced by Stefan Ropke and David Pisinger in their seminal works (Ropke and Pisinger, 2006a; Ropke and Pisinger, 2006b; Pisinger and Ropke, 2007) as an extension of the Large Neighborhood Search (LNS) (Shaw, 1998). Like its preceding method, ALNS deploys two sub-classes of operators: *destroy* and *repair.* A current solution will be destroyed by the destroy operators and then repaired using the repair operators. In this regard, the framework of ALNS allows us to utilize multiple neighborhoods within the same searching process in an adaptive way, where this adaptiveness is attained by recording the performance of each neighborhood and dynamically adjusting the selection of methods according to this record.

ALNS framework also offers several benefits for the designers of optimization algorithms. As noted by Pisinger and Ropke (2019), the adaptive selection of neighborhoods provides some extra freedom for the designers to incorporate more destroy and repair operators as the dynamic selection mechanism will limit the execution of ineffective operators. The insertion of multiple neighborhoods in ALNS also yields a benefit on the diversification of the searching process, reducing the chance of being trapped in local optima. Moreover, the *domain-free* structure of ALNS framework, which comprises several *convertible* operators at its core, provides flexibility for the designer to implement ALNS in various domains. This way, the designer of ALNS can also take advantage from previous knowledge of well-performing heuristic methods that can be embedded as a repair operator.

Considering the benefits of ALNS framework, it comes as no surprise that the popularity of ALNS for solving optimization problems has been continuously increasing. Although the first proposals of ALNS were devoted to transportation optimization problems, namely the Pickup and Delivery Problem with Time Windows (Ropke and Pisinger, 2006a) and the class of problems in Vehicle Routing Problems (Ropke and Pisinger, 2006b; Pisinger and Ropke, 2007), numerous researchers have exhibited the tremendous effectiveness of ALNS and the flexibility of this framework has been shown in multiple domains, such as manufacturing system (e.g., Rifai et al., 2016), healthcare (e.g., Lusby et al., 2016), and farming (e.g., Praseeratasang et al., 2019a; Praseeratasang et al., 2019b. Some researchers have also attempted to adopt ALNS to deal with multi-objective optimization problems (MOOPs) (e.g., Demir et al. 2014; and Rifai et al., 2016) and to extend the performance of ALNS in dealing with the characteristics of the addressed problems, ranging from proposing new operators (e.g. Coelho et al. 2012a; Coelho et al. 2012b; and Demir et al. 2012) to hybridizing ALNS with other approaches, such as exact

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Nomenclature

S	Feasible solution
S'	Newly obtained solution
S^*	Best-known solution
Ω^-	Set of destroy operators
Ω^+	Set of repair operators
w_i^-	The weight associated with destroy operator i
w_i^+	The weight associated with repair operator i
p^-	Probabilities of destroy operators to be selected
p^+	Probabilities of repair operators to be selected
η_s	Updating period of weights
T_0	Initial temperature
T	Current temperature
α	Cooling rate

methods (e.g., Keskin and Çatay, 2018; Keskin et al., 2019; Hammami et al., 2019; and Guastaroba et al., 2020) or other well-known meta-heuristics (e.g. SteadieSeifi et al., 2017; Avci and Avci, 2019). In this regard, it is safe to say that ALNS has become an attractive option for operational researchers and practitioners who deal with complex optimization problems.

Despite the wide range of works on ALNS, systematic surveys to map the advancement and the applications of ALNS are very limited. This gap motivates us to conduct this study. This study contributes by drawing a big picture of the current state of ALNS research that will provide researchers with a comprehensive understanding of the ALNS framework, which is crucial in expanding the development of ALNS itself.

To the best of our knowledge, this is the first systematic literature survey of ALNS. To date, Pisinger and Ropke (2019) and the *meta*-analysis of Turkeš et al. (2020) are the only two studies that intersect with this study. Pisinger and Ropke (2019) provided a formal introduction of ALNS framework and discussed the properties and some basic considerations in designing an ALNS-based algorithm. However, their review on some previous works is more focused on LNS framework, instead of ALNS. On the other hand, Turkeš et al. (2020) reviewed 95 ALNS-related studies to quantify the effect of the adaptive layer of ALNS, which implies different goal to our literature survey.

Our study is driven by the following research questions (RQs):

RQ 1: *"What is the intensity of publications related to ALNS?"*.

RQ 2: *"What are the current emerging trends of the development and application of ALNS?"*.

RQ 3: *"What are the potential directions that offer the opportunity to extend the progress of ALNS developments and applications?"*.

To answer these RQs, we conduct a systematic concept-centric review (Webster and Watson, 2002), which is performed based on the framework in Fig. 1. This concept-centric model involves the development of a concept matrix, which classifies the related works based on a pre-specified taxonomy in order to finding recognizable patterns from them. This method is selected due to its effectiveness in synthesizing the state-of-the-art of the literature on various topics (see Braekers et al., 2016; Mara et al., 2021). Furthermore, this type of systematic review enables us to enhance the quality, replicability, reliability, and validity of the review process which are crucial in synthesizing scientific knowledge (Xiao and Watson, 2019). Here, a taxonomical review on 252 scientific publications is performed to easily draw the state-of-the-art of ALNS research and map the potential research gaps. This study has four specific objectives: (1) to provide a big picture of ALNS research by analyzing the intensity and trends in terms of algorithm developments and applications, (2) to classify the ALNS literature using a taxonomical review, (3) to review the emerging trends of ALNS research, and (4) to point out several interesting research directions for the ALNS research community.

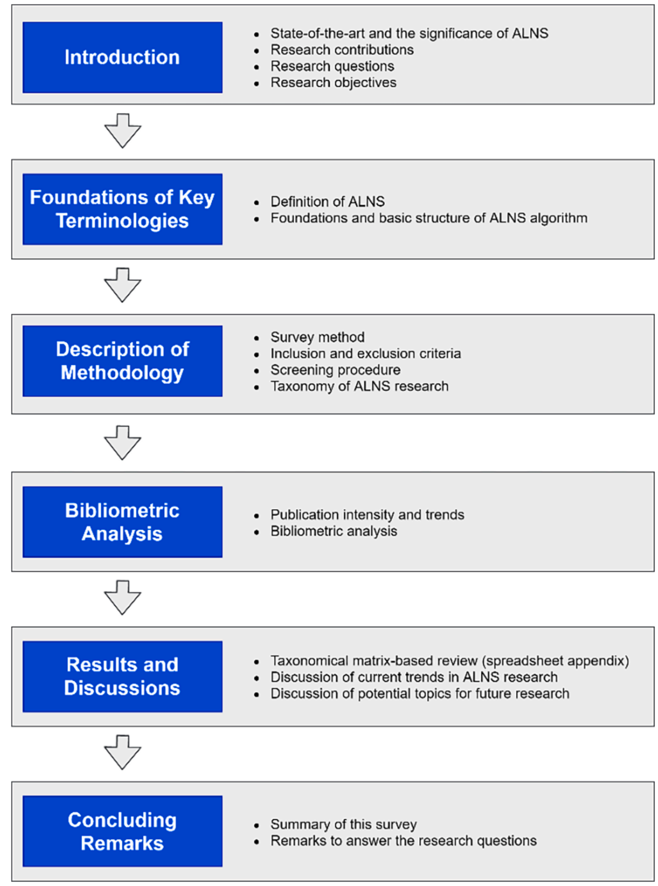

Fig. 1. Survey framework.

The remaining parts of this article are structured as follows. The historical perspective and the basic structure of ALNS are presented in Section 2. The scope of this survey and the taxonomy for ALNS research are described clearly in Section 3. Then, Section 4 presents the overview of publication intensity and trends in ALNS research, while Section 5 provides the results of the taxonomical review. Section 6 discusses the future research directions based on the results, and finally, Section 7 draws concluding remarks on this article.

2. Adaptive large neighborhood search

2.1. Foundations of ALNS

ALNS was originally developed from the LNS proposed by Shaw (1998). While several heuristics typically consist of neighborhood moves leading to small changes experienced by the considered solution, LNS itself belongs to very large-scale neighborhood search algorithms whose core concept is to consider large neighborhoods when exploring the solution search space (Pisinger and Ropke, 2007). The main benefit of considering the large neighborhood compared to small-neighborhood heuristics is that easier to navigate from one to another new promising area in the solution space of tightly constrained problems (Ropke and Pisinger, 2006a). However, the computational time of exploring large neighborhoods becomes the main trade-off when one considers implementing the large neighborhood-based heuristic.

Algorithm 1 presents the structure of LNS heuristic. The LNS developed by Shaw (1998) is built on a destroy and a repair operator. The destroy operator is first implemented to remove parts of a feasible solution S and the resulting solution is stored in S'. The repair operator then re-inserts the removed parts from the S' so that S' becomes a complete solution. Let $f(S)$, $f(S^{'})$, and $f(S^{*})$ be the objective of the current solution, the newly obtained solution, and the best-known solution insofar, respectively. Without the loss of generality, assume that the considered problem belongs to the minimization problem. A classical greedy acceptance criterion, i.e., only accepting the improving solution, is applied in the LNS heuristic, which is expressed in line 8 of Algorithm 1. These steps will repeat until the stop-criterion is met, e.g., the maximum number of iterations. ALNS, which is an extension of LNS, differs in several aspects. The extensions are further explained in Section 2.2.

Algorithm 1: The standard structure of LNS

1 **input**: a feasible solution S
2 $S^{*}\leftarrow S$, $S^{'}\leftarrow S$
3 **repeat**
4 $\quad S^{'}\leftarrow repair(destroy(S))$
5 $\quad$ **if** $accept(S^{'}, S)$ **then**
6 $\quad\quad S\leftarrow S^{'}$
7 $\quad$ **end if**
8 $\quad$ **if** $(f(S^{'})\langle f(S^{*}))$ **then**
9 $\quad\quad S^{*}\leftarrow S^{'}$
10 $\quad$ **end if**
11 **until** stop-criterion met
12 **return** S^{*}

2.2. Basic structure of ALNS

ALNS works by iteratively applying a destroy and a repair operator to improve the considered solution. Algorithm 2 shows the standard structure of the ALNS heuristic. Unlike its predecessor that only considers one destroy and one repair operator, the ALNS consists of *a set of destroy and a set of repair operators,* denoted by $\Omega^{-} = \{\Omega_1^{-}, \cdots, \Omega_{|\Omega^{-}|}^{-}\}$ and $\Omega^{+} = \{\Omega_1^{+}, \cdots, \Omega_{|\Omega^{+}|}^{+}\}$ respectively. The basic structure of ALNS will be hereafter explained by adopting the descriptions in Ropke and Pisinger (2006a), who pioneered the development of ALNS. Ropke and Pisinger (2006a) utilized the ALNS heuristic to solve the PDPTW. Three destroy operators and two repair operators were developed in the original form of ALNS. Since a solution of PDPTW consists of a sequence of pick-up and delivery requests, each destroy or repair operator implements a particular criterion to remove or insert requests from the considered solution. In every iteration of ALNS, it selects a single destroy and a single repair operator among the set of available operators, and a *roulette wheel selection principle* is utilized. The roulette wheel contains the probabilities of choosing each operator from the set of available operators, denoted as $p^{-} = \{p_1^{-}, \cdots, p_{|\Omega^{-}|}^{-}\}$ for the destroy operators and $p^{+} = \{p_1^{+}, \cdots, p_{|\Omega^{+}|}^{+}\}$ for the repair operators. These probabilities are assigned based on the corresponding weight w_i^{-} and w_i^{+} Which implies the historical performance of each operator. The value of each w_i^{-} and each w_i^{+} are initially set equal and then updated every η_s iterations. In this regard, the calculation of probabilities p_i^{-} and p_i^{+} Can formally be explained by Eqs. (1) and (2), where the formulas imply that the operator which contributes the most will have the highest probability to be selected.

$$p_i^{-} = \frac{w_i^{-}}{\sum_j^{|\Omega^{-}|} w_j^{-}} \tag{1}$$

$$p_i^{+} = \frac{w_i^{+}}{\sum_j^{|\Omega^{+}|} w_j^{+}} \tag{2}$$

Instead of adopting a classical acceptance criterion employed in Shaw (1998), the ALNS of Ropke and Pisinger (2006a) employs *Metropolis criteria* with the aim of reducing the possibility of getting trapped in a local optimum point. If $f(S^{'})\langle f(S^{*})$, the ALNS directly accepts the $S^{'}$ as S^{*}; otherwise, the ALNS gives the $S^{'}$ an acceptance probability of $e^{-(f(S^{'})-f(S))/T}$. Here, T represents the current temperature. Initially, T is set as the initial temperature T_0. In every iteration, T decreases gradually by multiplying the T with the cooling rate parameter α, where $0 < \alpha < 1$. The lower the T value is, the lower the probability of accepting a worse solution is. Therefore, the aim of utilizing these acceptance criteria is to allow the ALNS to widely explore the solution space in the early iterations and to focus on finding good-quality solutions in the later iterations.

Algorithm 2: The standard structure of ALNS

input: a feasible solution S, Ω^{-}, Ω^{+}, η_s, α, T_0
$S^{*}\leftarrow S$, $S^{'}\leftarrow S$, $i\leftarrow 1$, $T\leftarrow T_0$
Initialize w_i^{-}, w_i^{+}, p^{-}, and p^{+}
repeat
$\quad$ Select a destroy and a repair operator from Ω^{-} and Ω^{+} using roulette wheel selection
$\quad S^{'}\leftarrow repair(destroy(S))$
$\quad$ **if** $accept(S^{'}, S)$ **then**
$\quad\quad S\leftarrow S^{'}$
$\quad$ **If** $(f(S)\langle f(S^{*}))$ **then**
$\quad\quad S^{*}\leftarrow S$
$\quad$ **end if**
else
$\quad$ **if** $rand[0,1]\langle e^{-(f(S^{'})-f(S))/T}$ **then**
$\quad\quad S\leftarrow S^{'}$
$\quad$ **end if**
end if
if $i = \eta_s$ **then**
$\quad$ Update w_i^{-}, w_i^{+}, p^{-}, and p^{+}
$\quad\quad i = 0$
end if
$\quad T = \alpha T$, $i = i + 1$
until stop-criterion met
return S^{*}

3. Survey methodology

Our review is performed as a systematic concept-centric study (Webster and Watson, 2002), performed by closely following the eight-step process of a systematic literature review described by Xiao and Watson (2019): (i) formulate the problem, (ii) develop and validate the review protocol, (iii) search the literature, (iv) screen for inclusion, (v) assess quality, (vi) extract data, (vii) analyze and synthesize data, and (viii) report findings.

The core structure of our review consists of the classification of the considered literature based on a taxonomy of ALNS research. The classification results are then presented in a spreadsheet-based matrix that enables the interested readers to easily find a list of articles that suits their interests (Braekers et al., 2016). While providing a broad overview of a certain research area, this taxonomical analysis provides a lot of advantages for the research community. In general, the use of taxonomy enables researchers to efficiently store, learn, and recall established ideas. It also supports the expansion of knowledge by objectively pointing out the current voids and potential developments of a research area (Eksioglu et al., 2009). In this regard, we refer the readers to several previous surveys from Eksioglu et al. (2009) and Braekers et al. (2016) for the successful implementations of taxonomical analysis. Moreover, in the following subsections, the scope of this survey is discussed in detail in Subsection 3.1 and the presentation of the taxonomy of ALNS research is given in Subsection 3.2.

3.1. Scope of the survey

This subsection describes the scope of this survey. This consists of the explanation of the inclusion criteria of the literature and the screening procedure employed in this study.

3.1.1. Inclusion criteria

There are four inclusion criteria used for the purpose of this study. First, to ensure that this review is up to date while acknowledging our time constraint, only articles published online before 1 September 2021 were taken into account. Second, we only considered academic articles in English. Third, in order to make the number of publications manageable, only SCOPUS indexed journals and book chapters were considered in this article. Fourth, we distinguished ALNS from its primitive methods (VLNS and LNS) based on the implementation of adaptive selection of neighborhood operators, and therefore, only articles that implement ALNS were included in this survey.

3.1.2. Screening procedure

The search process of the articles was guided by two general keywords: "Adaptive Large Neighborhood Search" OR "ALNS". These keywords were deployed to perform a literature search in SCOPUS electronic database using Publish or Perish 7 software, resulting in a list of 741 papers. From this list, we performed a removal of duplicates and derived 617 unique papers. These articles were then reviewed based on their abstract and content, resulting in the initial list of 239 papers. Furthermore, a snowball approach was performed by checking articles cited by these 239 papers (backward movement) and articles citing these 239 papers (forward movement). In total, this search process resulted in a database of 252 journal articles published from 2006 to 2021.

3.2. Taxonomy of studies on ALNS

A simple taxonomy is proposed in this study to capture big picture of recent advances of the ALNS algorithm. This proposed taxonomy is featured in Fig. 2. As seen in Fig. 2, the first level of this taxonomy arranges the classification of ALNS articles based on the development and application of the ALNS algorithm. We draw such inspiration from the previous study of Abdullahi et al. (2020), who classified Symbiotic Organisms Search (SOS) algorithm literature based on the evolution (technical development) and the application of SOS. The second level of ALNS development consists of two sub-levels, namely the modification of ALNS structure (e.g., destroy and repair operators, adaptive mechanism, acceptance criterion, and termination criterion of the algorithm) and the hybridization with other optimization frameworks (see Raidl, 2015; Blum et al., 2011 for interesting discussions on hybrid metaheuristics). On the other hand, the second level of application aspect consists of the classification based on the considered optimization classes (single- or multi-objective optimization, discrete, continuous, or mixed search space, deterministic, stochastic, or mixed parameters) and application areas.

4. Publication intensity, trends, and bibliometric analysis

In this subsection, we present key statistics on ALNS publications. We deployed JabRef (https://www.jabref.org) to extract the raw data from 252 selected articles. Fig. 3 displays the publishing trend of ALNS from 2006 to 2021, in which the soaring popularity of ALNS as an optimization framework is obvious as the number of publications has generally

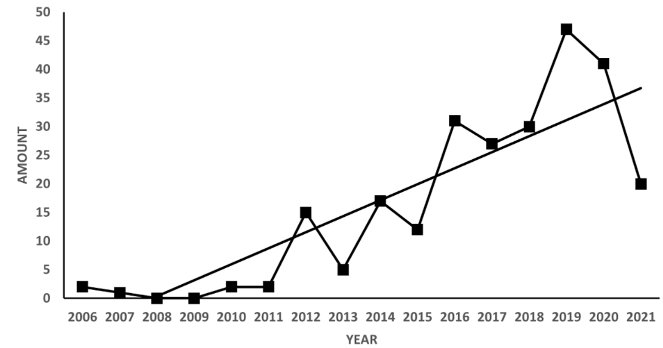

Fig. 3. Yearly publishing trend of ALNS publications.

been increasing. It must also be noted that the number of publications in year 2021 only includes the works that published in the first half of 2021. Interestingly, a huge leapfrog in the number of publications on ALNS can be seen in 2016, in which 31 articles were published, 158% higher than 12 articles published in 2015. This coincided with the seminal review from Sörensen (2015), which critically derided the proliferation of inventing "novel" nature-inspired metaheuristics and promoted the importance of neighborhood-based frameworks such as Variable Neighborhood Search. Looking back at the position of ALNS as a neighborhood-based metaheuristic framework, this observation seems to be in line with the finding of Hussain et al. (2019), who reviewed the publishing trend of metaheuristic research in general.

In terms of the type of study, among those 252 articles, we found only two articles (0.79%) from Santini et al. (2018) and Turkeš et al. (2020) that can be classified as a *meta*-analysis article. Santini et al. (2018) provided a comprehensive discussion on the selection of acceptance criteria to be used in ALNS, while Turkeš et al. (2020) explored the effectiveness of the mechanism to select destroy and repair operators *adaptively*. Apart from those two articles, the other 238 articles can be classified as an implementation article, in which the ALNS-based heuristic is deployed to solve certain optimization problems, whether as the main proposed algorithm (228 articles, 95%) or as a benchmark algorithm to test other approaches (see Ribeiro et al., 2014; Lee and Prabhu, 2016; Vilhelmsen et al., 2017; Xie et al., 2017; Chentli et al., 2018; Mousazadeh and Darestani, 2019; Kancharla and Ramadurai, 2020b; Lee et al., 2020; Nuraiman et al., 2020; Li et al., 2020).

Furthermore, this study also observes several key trends from the publishing point of view. Table 1 shows that most ALNS publications have been published by Elsevier (63.8%), while Table 2 displays ten key contributing journals insofar. Authorship-wise, Table 3 lists 10 authors who have been involved in the majority ALNS publications and identifies 10 key collaboration pairs. Our analysis finds that there are 495 different authors involved in ALNS publications, in which Gilbert

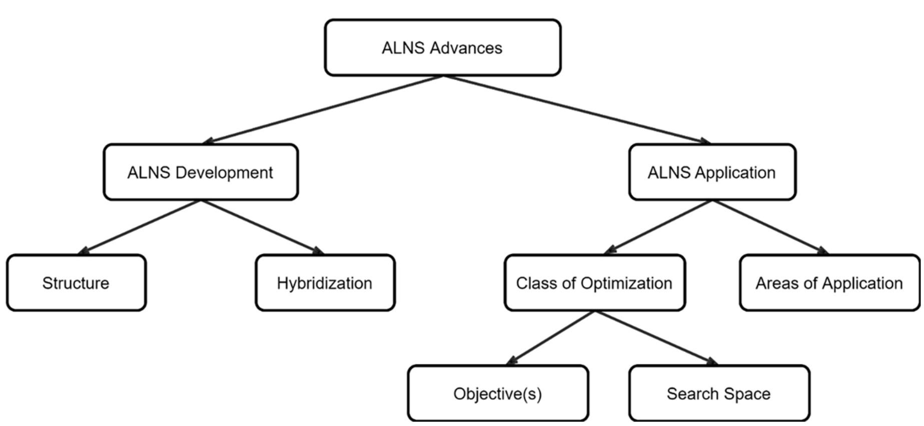

Fig. 2. Taxonomy of ALNS research.

Table 1
Publishers of ALNS publications.

Publisher	Number of Articles	Year															
		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Elsevier	159	1	1	0	0	0	2	11	2	10	8	29	17	19	23	22	14
Springer	25	0	0	0	0	1	0	2	2	1	0	0	4	5	3	7	0
Taylor & Francis	13	0	0	0	0	0	0	1	0	1	2	1	1	1	2	3	1
INFORMS	11	1	0	0	0	1	0	0	1	2	1	0	1	1	3	0	0
Wiley	10	0	0	0	0	0	0	0	0	3	0	0	3	0	2	2	0
MDPI	9	0	0	0	0	0	0	0	0	0	0	0	0	0	6	1	2
IEEE	7	0	0	0	0	0	0	1	0	0	0	0	0	0	4	2	0
Others	18	0	0	0	0	0	0	0	0	0	1	1	1	4	4	4	3
Total	252	2	1	0	0	2	2	15	5	17	12	31	27	30	47	41	20

Table 2
Key contributing journals.

Journal Name	Number of Articles	SJR 2019
Computers & Operations Research	53	1.66
European Journal of Operational Research	35	2.36
Transportation Research Part E: Logistics and Transportation Review	13	2.30
Transportation Research Part C: Emerging Technologies	12	3.34
Transportation Science	10	2.8
Expert Systems with Applications	8	1.49
Networks	7	0.84
Journal of Heuristics	6	0.67
Transportation Research Part B: Methodological	6	2.90
Computers and Industrial Engineering	5	1.47

Table 3
Key contributing authors and paired author.

Author	No. of Articles	Authors	No. of Joint Articles
Laporte, Gilbert	42	Jean-François Cordeau AND Gilbert Laporte	5
Cordeau, Jean François	13	David Pisinger AND Stefan Ropke	4
Coelho, Leandro C.	11	Ahmad Hemmati AND Lars Magnus Hvattum	4
Langevin, André	10	Emrah Demir AND Tom Van Woensel	4
Van Woensel, Tom	9	Emrah Demir AND Gilbert Laporte	4
Demir, Emrah	9	Ola Jabali AND Gilbert Laporte	4
Ropke, Stefan	9	Ola Jabali AND Cağri Koç	4
Hvattum, Lars Magnus	8	Merve Keskin AND Bülent Çatay	4
Bektaş, Tolga	6	Tolga Bektaş AND Gilbert Laporte	4
Gendreau, Michel	6	Gilbert Laporte AND Cağri Koç	4

Laporte has the highest involvement of 42 articles. Gilbert Laporte's collaboration with Jean-François Cordeau has also appeared in most articles so far with a total of five articles, while other key pairs identified are David Pisinger – Stefan Ropke (four articles), Merve Keskin – Bülent Çatay, Emrah Demir – Tom Van Woensel, Emrah Demir – Gilbert Laporte, and Ahmad Hemmati – Lars Magnus Hvattum, each has four collaborative articles.

It is also interesting to evaluate the popularity of each ALNS-related publication in detail. In Table 4, some of the most popular journal articles related to ALNS are presented alongside its keywords. Similarly, Table 5 displays 20 emerging articles that have received surging attentions from the ALNS research community. In this regard, we will call the articles belong to Tables 4 and 5 respectively as 'seminal papers' and 'emerging papers'. Seminal articles are included based on the number of citations of each paper, whereas articles are classified as emerging papers based on the number of citations per year and those which are published within the last five years.

The list of seminal articles in Table 4 reveals some interesting insights. Naturally, three articles that first introduced ALNS (Ropke and Pisinger, 2006a; Ropke and Pisinger, 2006b; Pisinger and Ropke, 2007) have received numerous citations and are included in the top five most cited articles. We also observe the presence of multiple articles related to the study of electric vehicles in Table 4, indicating the popularity and the importance of ALNS in this topic (Hiermann et al., 2016; Goeke and Schneider, 2015; Keskin and Çatay, 2016; Yang and Sun, 2015). Additionally, two seminal works from Demir et al. (2012) and Demir et al. (2014) present the implementation of ALNS in an important topic of sustainability in vehicle routing, in which these articles introduced the class of pollution-routing problems to minimize the CO2 emissions and fuel consumption from freight transportation activities. Some of the articles classified in the seminal papers can also be attributed to their contributions to the advancement of classical optimization problems, such as inventory-routing problems (Coelho et al., 2012a; Coelho et al., 2012b; Adulyasak et al., 2014a), vehicle routing problems (VRPs) (Mattos Ribeiro and Laporte, 2012), two-echelon routing problems (Contardo et al., 2012; Grangier et al., 2016), technician routing and scheduling problem (Kovacs et al., 2012), production-routing problem (Adulyasak et al., 2014b), and timetabling (Barrena et al., 2014).

Some of the articles included in Table 4 are also presented in Table 5. Two of these works are related to electric vehicle study (Hiermann et al., 2016; Keskin and Çatay, 2016), whereas another papers discussed the implementation of ALNS in city logistics (Grangier et al., 2016) and a memetic algorithm with ALNS for designing a resilient global supply chain network under uncertainty (Hasani and Khosrojerdi, 2016). Similar to the findings from Table 5, we observe that numerous emerging papers in Table 5 studied the implementation of electric vehicles (Jie et al., 2019; Zhang et al., 2020; Keskin et al., 2019; Guo et al., 2018; Schiffer and Walther, 2018b; Keskin and Çatay, 2018) or the environmental issue of routing activities (Franceschetti et al., 2017; Koç et al, 2016a; Liao et al., 2020). Two papers are related to the implementation of ALNS in solving a multi-objective optimization problem (Rifai et al., 2016; Liao et al., 2020), which is currently an emerging issue in operations research. Lastly, with respect to the work of Li et al. (2020) who implemented ALNS as a benchmark to test their proposal of artificial bee colony algorithm, other emerging papers in Table 5 are closely related to the particular advancement of combinatorial optimization models, such as the inclusion of multiple depots and multiple compartments in VRP (Alinaghian and Shokouhi, 2018), time-dependency in scheduling problem (Liu et al., 2017), synchronization of vehicle visits in VRP, (Liu et al., 2019a), profitability of logistics system (Li et al., 2016a), and the presence of drones in logistics (Sacramento et al., 2019). Overall, these insights imply the contributions of ALNS in solving emerging issues related to optimization.

Table 4
Top 20 cited articles.

Rank	Authors (Year)	Total Citations	Keywords
1	Ropke and Pisinger (2006b)	932	Pickup and delivery problems with time windows; Large neighborhood search; Metaheuristics
2	Pisinger and Ropke (2007)	785	Metaheuristics; Large neighborhood search; Vehicle routing problem
3	Demir et al. (2012)	347	Vehicle routing; Fuel consumption; CO2 emissions; Freight transportation; Heuristic algorithm
4	Demir et al. (2014)	273	Vehicle routing; Fuel consumption; CO2 emissions; Multicriteria optimization; Heuristics
5	Ropke and Pisinger (2006a)	265	Metaheuristics; Vehicle routing problems; Large neighborhood search
6	Hemmelmayr et al. (2012)	262	Two-Echelon Vehicle Routing Problem; Location Routing Problem; Adaptive large neighborhood search heuristic; City logistics
7	Hiermann et al. (2016)	227	Heterogenous fleet; Electric vehicle routing; Efficient constraint handling
8	Goeke and Schneider (2015)	211	Electric vehicles; Energy consumption; Green logistics; Metaheuristic; Vehicle routing
9	Keskin and Çatay (2016)	167	Electric vehicle; Vehicle routing problem with time windows; Adaptive large neighborhood search; Metaheuristics; Partial recharge
10	Mattos Ribeiro and Laporte (2012)	167	Adaptive large neighborhood search; Cumulative objective; Disaster relief; Metaheuristics
11	Yang and Sun (2015)	163	Electric vehicles; Battery swapping; Location-routing problem; Adaptive large neighborhood search
12	Coelho et al. (2012b)	156	Inventory-routing problem; Transshipment; ALNS; Heuristic
13	Adulyasak et al. (2014a)	145	Branch-and-cut; Integrated supply chain planning; Inventory routing; Multivehicle; Production routing; Symmetry breaking
14	Hasani and Khosrojerdi (2016)	142	Global supply chain network design; Robust optimization; Resilience strategies; Disruption management; Parallel memetic algorithm; Fitness landscape analysis
15	Coelho et al. (2012a)	132	Vendor-managed inventory systems; Inventory-routing; Consistency; Service quality; Adaptive large neighborhood search; Matheuristic
16	Barrena et al. (2014)	125	Adaptive large neighborhood search metaheuristic; Demand-based timetable; Passenger welfare; Rail rapid transit
17	Adulyasak et al. (2014b)	111	Adaptive large neighborhood search; Integrated supply chain planning; Network flow; Production routing
18	Contardo et al. (2012)	103	Adaptive large neighbourhood search; Branch-and-cut; Two-echelon capacitated location routing problem
19	Grangier et al. (2016)	101	Routing; Two- echelon VRP; Synchronization; City logistics; Adaptive large neighborhood search
20	Kovacs et al. (2012)	101	Large neighborhood search; Metaheuristics; Service technician routing and scheduling; Vehicle routing

Table 5
Top 20 emerging articles.

Rank	Authors (Year)	Total Citations	Keywords
1	Hiermann et al. (2016)	45.40	Heterogenous fleet; Electric vehicle routing; Efficient constraint handling
2	Keskin and Çatay (2016)	33.40	Electric vehicle; Vehicle routing problem with time windows; Adaptive large neighborhood search; Metaheuristics; Partial recharge
3	Sacramento et al. (2019)	30.50	Delivery operations; Vehicle routing problems with drones; UAVs; ALNS
4	Hasani and Khosrojerdi (2016)	28.40	Global supply chain network design; Robust optimization; Resilience strategies; Disruption management; Parallel memetic algorithm; Fitness landscape analysis
5	Li et al. (2020)	27.00	Vehicle routing problem; Time window; Synchronized visit; Artificial bee colony; Energy consumptions
6	Jie et al. (2019)	26.50	Routing; Two-echelon system; Electric vehicle city logistics; Column generation; Adaptive large neighborhood search
7	Liu et al. (2019b)	23.00	Vehicle routing; Synchronized-services; Time windows; Adaptive large neighborhood search
8	Zhang et al. (2020)	22.00	Vehicle routing problem; Credibility theory; Electric vehicle; Fuzzy simulation; Adaptive large neighborhood search
9	Keskin et al. (2019)	20.50	Time-dependent; Electric vehicle routing problem; Soft time windows; Queueing; Matheuristics
10	Grangier et al. (2016)	20.20	Routing; Two-echelon VRP; Synchronization; City logistics; Adaptive large neighborhood search
11	Franceschetti et al. (2017)	19.50	Routing; Freight transportation; Green vehicle routing; Greenhouse gases emissions; Metaheuristic algorithm; Departure time and speed optimization
12	Guo et al. (2018)	19.33	Electric vehicles; Battery charging station; Location model; Range anxiety; Distance deviation
13	Liu et al. (2017)	18.50	Agile satellite scheduling; Adaptive large neighborhood search; Time-dependent; Time slacks
14	Koç et al. (2016a)	18.40	Location-routing; Fuel consumption; CO2 emissions; Heterogeneous fleet; City logistics; Adaptive large neighborhood search metaheuristic
15	Schiffer and Walther (2018b)	18.00	Electric logistics fleets; Robust location routing; Green logistics
16	Keskin and Çatay (2018)	17.33	–
17	Rifai et al. (2016)	17.00	Multi-objective optimization; Distributed scheduling; Reentrant permutation flow shop; Adaptive large neighborhood search
18	Liao et al. (2020)	17.00	Green; MDRP; Multi-objective; NSGA-II; ALNS
19	Alinaghian and Shokouhi (2018)	16.67	Multi depot vehicle routing problem; Multi compartment; Adaptive large neighborhood search
20	Li et al. (2016a)	16.40	Vehicle routing problem; Pickup and delivery problem; Time window; Profit; Adaptive large neighborhood search

5. Results and discussions

The classification of 252 articles related to ALNS was conducted based on the taxonomy described in Section 4. The key findings from this classification are discussed in this section. The discussion presents the overview of the technical development of ALNS insofar (Subsection 5.1) and the ALNS application (Subsection 5.2), respectively. The emerging trends of ALNS research is then presented in Subsection 5.3. Further, the complete results of this classification process are documented in a spreadsheet-based file and are available as an Electronic Appendix.

5.1. Overview of ALNS development

In this subsection, the technical development of ALNS is reviewed and analyzed. The discussion is separated into two aspects, namely, the development of the structure of ALNS-based algorithms (Subsection 5.2.1) and the hybridization of ALNS with other methods (Subsection 5.2.2).

5.1.1. Structure development

As seen in Algorithm 2, the standard structure of ALNS comprises at least four important parts. These parts are: (a) the adaptive mechanism for selecting the deployed operators (see line 5), (b) the criterion to accept a newly obtained solution (see line 7–15), (c) the stopping criterion of the algorithm (see line 22), and (d) the design of destroy and repair operators to be used in sets Ω^- and Ω^+. During our study, we observed that the ALNS research community had been rapidly developing the selection of these aspects, except for the design of the adaptive mechanism. Table 6 provides a complete overview of the ALNS structure.

- *Adaptive Mechanism*

Our results suggest that only a single article from Chowdhury et al. (2019) investigated an adaptive mechanism to select the destroy and repair operators to be deployed, namely a stochastic universal sampling strategy introduced by Baker (1987). Meanwhile, another article chose to implement the classical roulette wheel mechanism as in the standard form of ALNS (Ropke and Pisinger, 2006a). Similar with the principle of a roulette wheel, the stochastic universal sampling also consists of assigning a set of probabilities to a set of neighborhood operators, with the aim to select the considered neighborhood operators (in this case, the sets of destroy and repair operators). However, the main difference of the stochastic universal sampling is that it employs multiple N equally spaced pointers instead of a single pointer as in the roulette wheel, resulting in a reduction of bias in the selection process of operators (for the complete discussion of the stochastic universal sampling technique, we refer the reader to the study of Pencheva et al. (2009)). Motivated by the reduction of bias, Chowdhury et al. (2019) explored the effectiveness of using the stochastic universal sampling strategy in two-hybrid heuristics based on the ALNS and ant colony optimization (ACO) metaheuristic (Dorigo and Di Caro, 1999). They compared the results to similar heuristics equipped with a roulette wheel mechanism. However, their results provided no conclusive evidence that the heuristics with the stochastic universal sampling strategy perform better than the one with roulette wheel mechanism.

Another interesting study that focused on the adaptive mechanism of ALNS is the *meta*-analysis from Turkeš et al. (2020). In the attempt of promoting the importance of a systematic statistic examination of a certain component within a metaheuristic framework, Turkeš et al. (2020) conducted an extensive study on the adaptive layer of ALNS, based on 134 studies with 25 different implementations of ALNS. They studied the “average improvement of the objective function caused by the adaptive layer” to see whether the presence of adaptive mechanism (in particular, the task of updating the weights and probabilities) in ALNS provides a significant contribution or not. Their results concluded that the presence of an adaptive mechanism contributed to 0.14% improvement of objective value and is recommended to be included in several specific situations.

- *Acceptance Criterion*

As seen in Algorithm 2, the standard pseudocode of ALNS in Ropke and Pisinger (2006a) comprises the Metropolis criterion to decide whether the new solution S' will be accepted as the incumbent solution or not. The use of Metropolis criterion, which is also widely known as the ***simulated annealing criterion*** (Kirkpatrick et al., 1983), is generally motivated by the effort to avoid being trapped in a local optimum point, as this criterion provides an opportunity to accept a worse solution based on the current annealing temperature T and the objective values of S and S'. Nevertheless, it is known that other acceptance criteria also exist, such as the standard greedy acceptance employed in the standard form of LNS (Algorithm 1). Therefore, the selection of a criterion to accept the newly obtained solution of ALNS becomes another important issue in designing an ALNS-based heuristic.

This issue was highlighted by the study of Santini et al. (2019). As there was no single guideline for selecting the acceptance criterion of ALNS-based heuristic, they conducted a computational study to compare nine different solution acceptance mechanisms, namely the hill climbing, random walk, late acceptance hill climbing, threshold acceptance (TA), Metropolis criterion, great deluge, non-linear great deluge, record-to-record travel (RRT), and worse accept. Their study recommended that adding the Metropolis criterion, TA, or RRT criteria are proven to be beneficial for the performance of the ALNS-based heuristic. On the other hand, random walk and hill climbing consistently show worse performance compared to other criteria. This experimental result shows that allowing the acceptance of worse solutions under specific conditions is an important consideration for designing a good acceptance criterion of the ALNS. They also particularly endorsed the use of the RRT criterion, which provided the best results in their experiments on the capacitated vehicle routing problem, capacitated minimum spanning tree problem, and quadratic assignment problem. Nevertheless, Santini et al. (2019) also noted that their results did not serve as a strict guideline to all forms of implementation but rather serve as a recommendation for problem variants closely related to those mentioned problems.

In line with the finding of Santini et al. (2018), our review also found that Metropolis criterion (81.35%), RRT (7.94%) (see Laporte et al., 2010; Hongtao et al., 2011; Contardo et al., 2012; Hemmelmayr et al., 2012; Lei et al., 2012; Salazar-Aguilar et al., 2012; Angélica Salazar-Aguilar et al., 2014; Chen et al., 2014; Lei et al., 2015; Braaten et al., 2017; Hemmati and Hvattum, 2017; Zhou et al., 2018; Zhu and Sheu, 2018; Chen et al., 2019; Kancharla and Ramadurai, 2019; Chen et al., 2020; Khajepour et al., 2020; Kuhn et al., 2020; Sarasola and Doerner, 2020; Al Chami et al., 2021), and TA (1.19%) (see Santini, 2019; Gansterer et al., 2020; Theeraviriya et al., 2020) are the three most popular acceptance criteria in ALNS, alongside the classical greedy acceptance for single-objective optimization problems (7.94%) (see

Table 6
Overview of ALNS structure.

The aspect of ALNS Structure	Options	Numbers of Papers	Relative Presence
Adaptive Mechanism	Roulette Wheel	250	99,21%
	Other Mechanism	1	0,40%
Acceptance Criterion	Greedy Mechanism	20	7,94%
	Metropolis Criterion	205	81,35%
	Record-to-Record	20	7,94%
	Threshold Acceptance	3	1,19%
	Pareto Domination	3	1,19%
	Other Mechanism	6	2,38%
Termination Criterion	Number of Iterations	188	74,60%
	Number of Non-Improving Iterations	48	19,05%
	Running Time Limit	49	19,44%
	Annealing Temperature	25	9,92%
	Other Mechanism	3	1,19%

Katterbauer et al., 2012; Muller et al., 2012; Qu and Bard, 2012; Qu and Bard, 2013; Nolz et al., 2014; Belo-Filho et al., 2015; Cherkesly et al., 2015; Lee and Kim, 2015; Chaharsooghi et al., 2016; Hasani and Khosrojerdi, 2016; Yu et al., 2017; Momayezi et al., 2021; Schiffer and Walther, 2018a; Schiffer et al., 2018; Schiffer and Walther, 2018b; Vareias et al., 2019; Yahiaoui et al., 2019; Hansen et al., 2020; Mourad et al., 2021; Theeraviriya et al., 2020) and the Pareto dominance principle for MOOPs (1.25%) (see Buer and Kopfer, 2014; Cota et al., 2019; Ji et al., 2019a). Further, in Table 7, we provide a review of five common acceptance criteria to be used in designing an ALNS-based algorithm.

- *Termination Criterion*

Another important aspect to be considered in implementing an ALNS-based heuristic, as well as in other forms of optimization algorithm, is the selection of termination criterion to be deployed. The selection of termination criterion, or also known as the *stopping criterion,* of a heuristic algorithm is generally seen as a user- and resources-dependent decision (Parsopoulos, 2016), where a trade-off between the effort to avoid unintentional premature termination (the algorithm is terminated before reaching its convergence) and unnecessary use of computational resources plays a huge part. Therefore, careful consideration of this aspect is required (Kwok et al., 2007).

Our results found that there are four widely used termination criteria in ALNS. These criteria are the number of iterations (74.60%), the number of non-improving iterations (19.05%), running time limit (19.44%), and the lower bound of annealing temperature (9.92%) due to the popularity of embedding the ALNS within a simulated annealing (SA) framework. Another mechanism that we found was terminating the searching process whenever it reaches a particular objective value (see Li et al., 2016b; Santos and de Carvalho, 2018; Li et al., 2020), which is obviously only possible if preliminary knowledge on the searching space is available.

- *Destroy and Repair Operators*

The anatomy of ALNS, as a neighborhood search algorithm, comprises a set of destroy and repair operators (destructive and constructive heuristics) for exploring the search space. Naturally, one issue that must be answered is the selection of the operators to be included (the structure of the neighborhood), which will influence the intensity and the diversity of the searching process. Pisinger and Ropke (2007) clearly stated that in order to develop an ALNS-based heuristic, the designer needs to:

(i) "Choose a number of fast constructive heuristics which are able to construct a full solution given a partial solution (a solution where some variables are set to $\perp$ and some have a real value)."
(ii) "Choose a number of destructive heuristics. It might be worthwhile to choose to destructive heuristics that are expected to work the chosen construction heuristics, but it is not necessary".
(iii) "Choose a local search framework at the master level."

Related to this issue in points (i) and (ii) above, Ahuja et al. (2002) provided a stimulating discussion regarding the development of neighborhood structure in their survey. Ahuja et al. (2002) emphasized the potential trade-off between the solution's quality obtained and the computational cost required. They noted that as the neighborhood structure grows larger, the better is the quality of the final solution potentially acquired. However, at the same time, employing a larger neighborhood structure also leads to a longer computational time required to search the neighborhood at each iteration. Therefore, employing a larger neighborhood structure does not guarantee the production of a more effective heuristic algorithm unless one can explore the larger neighborhood in a very efficient way, which implies the importance of the selection of destroy and repair operators in ALNS (Pisinger and Ropke, 2019).

Based on the reviewed literature, we observe that the idea of creating new operators is one of innovative aspects usually offered in ALNS and the process itself strongly relies on the characteristics of the problem. We draw several works dealing with vehicle routing problem variants, e.g. Demir et al. (2012), Keskin and Çatay (2016), and Hammami et al. (2019), to show representative illustrations of the development of new operators. In particular, Demir et al. (2012) developed new operators based on the spatial relationship among customer nodes. Keskin and Çatay (2016) proposed new operators for enabling the changes on the visits to recharging stations due to the nature of the problem addressed, i.e. considering a set of electric vehicles in the VRP. Hammami et al. (2019) addressed a VRP variant with two specific characteristics: (1) not all customers must be visited, and (2) the objective is to maximize the profit and utilized these problem-specific features to develop new operators. Based on the discussed works, one may employ specific feature (s) of the problem addressed in order to propose new destroy and repair operators for the ALNS.

Nevertheless, we note that the unavailability of a guideline to select the proper operators for each type of problem has largely been impacting the variability of ALNS-based heuristic designs. We observed that two seminal works of Ropke and Pisinger (2006a; 2006b) respectively employed five and three different destroy operators such as *random removal, shaw removal, worst removal, cluster removal, and history-based removal*, alongside two repair operators, namely the *greedy insertion and k-regret insertion.* In fact, our review reveals that the number of destroy operators employed in the 252 reviewed papers varied between $[1,13]$ different operators, with roundup average and standard deviation values of 6 and 2.75, respectively. On the other hand, the number of repair operators also varied [1,10], with roundup average and standard deviation values of 4 and 1.63, respectively. Further, we also found a handful of studies (Salazar-Aguilar et al., 2013; Riquelme-Rodríguez et al., 2014; Belo-Filho et al., 2015; Quirion-Blais et al., 2015; Riquelme-Rodríguez et al., 2016; Matusiak et al., 2017; Belhaiza, 2019) who designed ALNS using integrated destroy and repair operators, instead of selecting them separately (using separate roulette wheel mechanisms) as in the standard form of ALNS (see Ropke and Pisinger, 2006a; 2006b). Interested readers are referred to the first sheet of our Electronic Appendix to see the full list of neighborhood operators employed in the reviewed papers. Some commonly used destroy and repair operators are also available in Table 8.

All in all, we observe several interesting trends on the development of ALNS structure as follows:

Table 7
Overview of common acceptance criteria (minimization problem).

Criterion Name	Description	Reference(s)
Greedy acceptance	Accept the new solution $S^{'}$ only if $f(S^{'})\langle f(S)$	–
Metropolis criterion	Accept the new solution $S^{'}$ if $f(S^{'})\langle f(S)$, else calculate a random number $[0,1]$ and accept the new solution $S^{'}$ if $rand[0,1]\langle e^{-(f(S^{'})-f(S))/T}$	Kirkpatrick et al. (1983); Ropke and Pisinger (2006a)
Record-to-record	Accept the new solution $S^{'}$ if $\frac{f(S^{'})-f(S^{*})}{f(S^{'})}<R$, where R is a pre-determined threshold	Dueck (1993)
Threshold acceptance	Accept the new solution $S^{'}$ if $\frac{f(S^{'})-f(S^{*})}{f(S^{'})}<R$, where R is a pre-determined threshold and the value of R decreases at every iteration	Dueck and Scheuer (1990)
Pareto dominance	Accept the new solution $S^{'}$ if the relations $\forall_{o=1}^{O} f_o(S^{'})\leqslant f_o(S)$ and $\exists_{o=1}^{O} f_o(S^{'})\langle f_o(S)$ fulfilled, or in other words, $S^{'}$ dominates $S(S^{'}\prec S)$	Censor (1977); Deb (2008)

Table 8
Overview of common destroy and repair operators.

Destroy Operators

Name	Description	Reference(s)
Random removal	This operator iteratively removes a randomly selected node from a solution.	Ropke and Pisinger (2006a; 2006b)
Worst removal	This operator iteratively removes a node that significantly contributes to the total cost from a solution.	Ropke and Pisinger (2006a; 2006b)
Shaw removal	This operator iteratively removes a node that has the highest similarity index from a solution. The similarity index of a node is calculated by comparing the node with a selected seed node based on a set of predetermined criteria.	Shaw (1998), Ropke and Pisinger (2006a; 2006b)
Route removal	This operator is commonly found in the vehicle routing domain randomly and removes a number of routes with all the associated nodes from a solution.	Demir et al. (2012)
History-based removal	This operator iteratively removes a node that possesses the highest difference value between its current position cost and its historical best position cost from a solution.	Ropke and Pisinger (2006a), Pisinger and Ropke (2007)
Neighborhood removal	This operator originally proposed in the vehicle routing domain and iteratively removes a node that is significant with respect to the average distance of a route to where the node belongs to.	Demir et al. (2012)
Proximity-based removal	This operator is a special case of Shaw removal where the distance value between two nodes is the only criterion used as the similarity index.	Demir et al. (2012)
Time-based removal	This operator is a special case of Shaw removal where time characteristic difference between two nodes, e.g., the earliest time to start the service, is the only criterion used as the similarity index.	Demir et al. (2012)
Demand-based removal	This operator is a special case of Shaw removal where the demand difference between two nodes is the only criterion used as a similarity index.	Demir et al. (2012)
Cluster removal	This operator makes use of a clustering algorithm, e.g., Kruskal's algorithm, to create two clusters and remove all nodes contained in a randomly selected cluster from the solution.	Ropke and Pisinger (2006a), Pisinger and Ropke (2007)

Repair Operators

Name	Description	Reference(s)
Greedy insertion	This operator iteratively selects and inserts a node that has the least insertion cost among all remaining nodes in the removed nodes list to the solution. In some papers, this operator is called *Best insertion* or *Cheapest insertion.*	Ropke and Pisinger (2006a; 2006b), Pisinger and Ropke (2007)
(k-)Regret insertion	This operator iteratively selects and inserts a node that possesses the largest regret value among remaining nodes in the removed nodes list. The regret value of a node is obtained by taking the difference between the cost resulting from the best insertion position and the cost resulting from the *k*-best insertion position.	Ropke and Pisinger (2006a; 2006b), Pisinger and Ropke (2007)
Random insertion	This operator randomly selects a node from the removed nodes list and inserts the node at the position resulting to the lowest incremental cost.	Coelho et al. (2012a; 2012b), Qu and Bard (2012; 2013)
Sequential insertion	This operator sequentially inserts nodes from the removed nodes list at the least cost insertion position into the solution.	Kovacs et al. (2012)
Shaw insertion	This operator uses the similarity index concept described in Shaw removal to select the next node from the removed nodes list to be inserted into the solution.	Coelho et al. (2012a; 2012b)
Swap insertion	This operator randomly selects and swaps two nodes in the solution.	Coelho et al. (2012a)
Zone insertion	This operator originally proposed for a vehicle routing domain is similar to Greedy insertion but employs the time windows criterion rather than distance to determine the best insertion of a node.	Demir et al. (2012)
Cluster insertion	This operator classifies the removed nodes into a number of clusters before performing insertions.	Maknoon and Laporte (2017), Santini (2019)

- Two studies from Turkeš et al. (2020) and Santini et al. (2019) moved forward to analyze the impact of a certaint 'component' of ALNS. Turkeš et al. (2020) discussed the importance of injecting adaptive mechanism, while Santini et al. (2019) discussed the consideration of selecting an appropriate acceptance criterion in designing an ALNS-based algorithm. The presence of these two *meta*-analysis studies indicated that a portion of the ALNS research community has progressed to improve their understanding on the behavior of ALNS algorithm. This healthy precedence also indicated that the research community of ALNS may now enter the 'scientific-era' of metaheuristics mentioned by Sörensen et al. (2018).
- We also observe that the research community of ALNS has not reached any consensus on the selection of destroy-repair operators. Our review suggested the occurrence of high variability in the design process of ALNS operators, which might reduce the reproducibility of the proposed algorithms and create a barrier for non-expert practitioners in implementing ALNS (Sörensen et al., 2018). This situation provides an interesting research gap to be filled by future researchers.

5.1.2. *Hybridization*

The idea of hybridizing two or more algorithmic components into a single metaheuristic is a classical approach commonly referred to as a *hybrid metaheuristic*. The development of a hybrid metaheuristic is mainly motivated by the need to exploit the complementary character of different optimization techniques (Blum et al., 2011). Moreover, although it has been noted by Blum et al. (2011) that this effort to develop an effective hybrid metaheuristic is not trivial and requires expertise from various areas, this approach is still widely known to be a good alternative in producing a solution for complex optimization problems. Readers can read the recent surveys from Raidl (2015) and Pellerin et al. (2020) to see the latest development of hybrid metaheuristics.

The ALNS itself is largely associated with the concept of hybrid metaheuristic. As an extension of the LNS algorithm, the design process of ALNS requires us to select a local search framework at the master level (see Subsection 5.1.2), in which the ALNS framework will be embedded into the selected framework. The standard framework from Ropke and Pisinger (2006a) implemented the ALNS into the framework of SA (Kirkpatrick et al., 1983), which implies that the standard ALNS framework itself can also be classified as a hybrid metaheuristic. Further, Pisinger and Ropke (2007) also mentioned that the ALNS could be embedded into any local search framework other than SA, such as tabu search or guided local search, which emphasizes the flexibility of this approach. In this study, we also attempted to review the effort of the research community to hybrid the ALNS with other forms of the method. We classified the hybridization into four different classes as follows: (i) *exact method,* (ii) *local search procedure*, (iii) *other metaheuristics*, and (iv) *simulation procedure*. Table 9 presents the complete results of our classification on this aspect.

In several cases, ALNS is equipped with exact mathematical method (s), which guarantees a global optimum solution to strengthen the searching process. This approach is generally referred to as a *matheuristic algorithm*, which is defined by Boschetti et al. (2009) as a "heuristic algorithm made by the interoperation of metaheuristics and mathematical programming techniques." The effectiveness of the matheuristic

Table 9
Overview of hybridization on ALNS.

Hybridized Method	References	Numbers of Papers	Relative Presence
Exact Method	Katterbauer et al. (2012), Muller et al. (2012), Pillac et al. (2013), Pereira et al. (2015), Hemmati et al. (2016), Mancini (2016), Wen et al. (2016), Ziebuhr and Kopfer (2016), Gullhav et al. (2017), Leao et al. (2017), Hojabri et al. (2018), Keskin and Çatay (2018), Koc et al. (2018), Schiffer and Walther (2018a), Schiffer and Walther (2018b), Canca et al. (2019), Ghiami et al. (2019), Gu et al. (2019), Hammami et al. (2019), Jie et al. (2019), Keskin et al. (2019), Koç et al. (2019), Rohmer et al. (2019), Vareias et al. (2019), Zhao and Lu (2019), Guastaroba et al. (2020), Hà et al. (2020), Shao and Dessouky (2020), Vincent et al. (2021)	29	11,51%
Local Search Procedure	Cordeau et al. (2011), Qu and Bard (2013), Ribeiro et al. (2014), Taş et al. (2014), Lee and Kim (2015), Hiermann et al. (2016), Li et al. (2016a), Braaten et al. (2017), Gullhav et al. (2017), Smith and Imeson (2017), Alinaghian and Shokouhi (2018), Chen et al. (2018), Kisialiou et al. (2018a), Kisialiou et al. (2018b), Naccache et al. (2018), Santos and de Carvalho (2018), Schiffer and Walther (2018a), Schiffer et al. (2018), Schiffer and Walther (2018b), Soriano et al. (2018), Avci and Avci (2019), Cota et al. (2019), François et al. (2019), Gu et al. (2019), Hammami et al. (2019), Hof and Schneider (2019), Lahyani et al. (2019), Santini (2019), Yahiaoui et al. (2019), Zhao and Lu (2019), Eshtehadi et al. (2020), Graf (2020), Hammami et al. (2020), Kuhn et al. (2020), Masmoudi et al. (2020), Posada and Häll (2020), Sun et al. (2020), Cinar et al. (2021), Pan et al. (2021), Santos and de Carvalho (2021), Şatir Akpunar and Akpinar (2021), Al Chami et al. (2021), Chowmali and Sukto (2021), Vincent et al. (2021), Suksee and Sindhuchao (2021)	45	17,86%
Other Metaheuristics	Buer and Kopfer (2014), Cherkesly et al. (2015), Hasani and Khosrojerdi (2016), Lee et al. (2016), Kır et al. (2017), SteadieSeifi et al. (2017), Žulj et al. (2018), Chowdhury et al. (2019), Cota et al. (2019), He et al. (2019), Ji et al. (2019a), Ji et al. (2019b), Mofid-Nakhaee and Barzinpour (2019), Pitakaso and Sethanan (2019), Praseeratasang et al. (2019a), Thongkham and Srivarapongse (2019), He et al. (2020), Liao et al. (2020), Nanthapodej et al. (2021)	19	7,54%
Simulation Procedure	Kisialiou et al. (2018a), Kisialiou et al. (2019), Nasri et al. (2020), Keskin et al. (2021)	4	1,59%

approach has been a subject of interest for the research community of operational research in general, and several surveys are available on this topic (see Ball 2011; Archetti and Speranza, 2014). In total, we find 29 implementations of ALNS-based heuristic that could be classified as a matheuristic approach (Katterbauer et al., 2012; Muller et al., 2012; Pillac et al., 2013; Pereira et al., 2015; Hemmati et al., 2016; Mancini, 2016; Wen et al., 2016; Ziebuhr and Kopfer, 2016; Gullhav et al., 2017; Leao et al., 2017; Hojabri et al., 2018; Keskin and Çatay, 2018; Koc et al., 2018; Schiffer and Walther, 2018a; Schiffer and Walther, 2018b; Canca et al., 2019; Ghiami et al., 2019; Gu et al., 2019; Hammami et al., 2019; Jie et al., 2019; Keskin et al., 2019; Koç et al., 2019; Rohmer et al., 2019; Vareias et al., 2019; Zhao and Lu, 2019; Guastaroba et al., 2020; Hà et al., 2020; Shao and Dessouky, 2020; Vincent et al., 2021).

Our findings reveal that the exact method implemented varied, including the execution of mathematical programming model (e.g., mixed-integer linear programming model, integer programming model) using a commercial solver (e.g., GUROBI, CPLEX, Lingo) and the incorporation of other classical methods such as constraint programming (Hojabri et al., 2018), linear programming (Hà et al., 2020), dynamic programming methods (Schiffer and Walther, 2018a; 2018b), or column generation (Ziebuhr and Kopfer, 2016; Leao et al., 2017; Jie et al., 2019) into the framework of ALNS. Further, exact methods integrated in the ALNS are commonly employed in three different phases. First phase is to build an initial solution (Hemmati et al., 2016; Mancini, 2016; Ghiami et al., 2019; Rohmer et al., 2019). For the initialization procedure, general ways include decomposing the problem into a set of subproblems and solving one or more than one subproblems separately using the exact method while the remaining subproblems are solved heuristically. Second, exact methods are implemented as a post-optimization procedure to improve the potentially good solution (Muller et al., 2012; Pillac et al., 2013; Pereira et al., 2015; Wen et al., 2016; Keskin and Çatay, 2018; Koc et al., 2018; Schiffer and Walther, 2018a; Schiffer and Walther, 2018b; Canca et al., 2019; Gu et al., 2019; Hammami et al., 2019; Keskin et al., 2019; Koç et al., 2019; Vareias et al., 2019; Zhao and Lu, 2019; Shao and Dessouky, 2020). The post-optimization procedures are typically implemented after the repair phase is executed or after the ALNS ends. The former attempts to intensify the new solution produced after a destroy-repair phase while the latter focuses in improving the best solution produced by the ALNS. Lastly, the exact methods act as a part of repair operators (Katterbauer et al., 2012; Gullhav et al., 2017; Hojabri et al., 2018; Guastaroba et al., 2020; Hà et al., 2020). When an exact method is utilized in the repair phase, it aims to substitute/complement the heuristic-based repair operators by optimally re-inserting the destroyed parts of a solution. One important consideration when integrating an exact method is deciding which subproblem(s) to be solved in order to keep the computational time reasonable. This concern becomes one of the most prioritized aspects when the exact method is integrated as part of repair phase due to the iterative executions of the phase in ALNS.

We observed that the use of the exact method to improve the quality of the solution obtained by ALNS was the most popular strategy found in the reviewed papers. This finding is similar to the other alternative strategy which seems to be popular in the ALNS research community: enhancing the potentially good solution with a local search procedure. As seen in Table 9, we observed 45 studies (17.86%) that designed an ALNS-based algorithm and introduced the strategy into their designs. The main concept of only utilizing potentially good solution is to save computational time for intensifying solutions which only have small opportunity to improve the best solution so far obtained. Two common ways employed by the extant literature to determine a potentially good solution are: (1) the objective value of the new solution is better than that of the best solution so far and (2) the objective value of the new solution is still within a predetermined threshold value. However, some other works still include a strategy in which the local search procedure is implemented to every solution produced after the destroy and repair phases. Consequently, the computational cost certainly becomes the main concern when one wants to design the latter local search procedure implementation. In terms of the implementation, the selection of local search procedure varied from a set of local search moves which is executed iteratively to a formal procedure, such as the variable neighborhood search (see Alinaghian and Shokouhi, 2018; Avci and Avci, 2019).

Another popular strategy to be pursued is to hybridize the ALNS with other metaheuristic frameworks. Overall, we found 19 studies (7.54%) that attempted to embed the ALNS into another algorithmic framework at the master level (see Cherkesly et al., 2015; Hasani and Khosrojerdi, 2016; Lee et al., 2016; Kır et al., 2017; Chowdhury et al., 2019) or the other way around (see SteadieSeifi et al., 2017; Mofid-Nakhaee and Barzinpour, 2019). We also observed that tabu search (TS) was the most popular framework to be engaged with ALNS (see Kır et al., 2017; SteadieSeifi et al., 2017; Žulj et al., 2018; Pitakaso and Sethanan, 2019; He et al., 2020). In this extant literature, two types of strategy are commonly proposed, either embedding the TS as a local search procedure or revising the mechanism of a destroy or a repair operator to include the concept of TS. These strategies show two different levels of integration, i.e. adding the TS as a separate component in the ALNS or tightly combining the concept of TS into existing components of the ALNS. There were some studies which attempted to integrate the concept of ALNS (which traditionally belongs to the class of trajectory optimization algorithm) into a population-based framework as a local search procedure to intensify the searching process, such as the classical genetic algorithm (Lee et al., 2016), the more recent biased-randomized key genetic algorithm (He et al., 2019), differential evolution (Thongkham and Srivarapongse, 2019), and greedy randomized adaptive search procedure (Buer and Kopfer, 2014; Cherkesly et al., 2015). Note that since the standard form of ALNS (see Algorithm 2) is embedded into a SA framework, we did not consider the implementation of ALNS within an SA framework (which was still the most common strategy according to our observation) as an attempt of hybridization. Moreover, we also found three studies that incorporated ALNS into a MOOP algorithm, such as the non-dominated sorting genetic algorithm-II (Liao et al., 2020), a multi-objective evolutionary algorithm with decomposition (Cota et al., 2019), and binary borg evolutionary algorithm (Ji et al., 2019a).

Additionally, we also observed four works from Kisialiou et al. (2018a; 2019), Nasri et al. (2020), and Keskin et al. (2021) that incorporated the ALNS with a simulation procedure. Three studies (Kisialiou et al., 2018a; 2019; Keskin et al., 2021) successfully implemented a discrete event simulation procedure in order to cope with the uncertainty of input parameters, such as the waiting times at a recharging station of electric vehicles (Keskin et al., 2021), the sailing and service times of a voyage due to the uncertainty in weather condition (Kisialiou et al., 2018a), and the demand of customers (Kisialiou et al., 2019), while Nasri et al. (2020) decided to implement a Monte Carlo simulation to develop a robust approach.

In conclusion, from these findings, we can draw the state-of-the-art of hybridization aspect of ALNS. Some insights on the emerging trends of ALNS research can be derived as follows:

- It is suggested that the inclusion of a post-optimization strategy can be an effective strategy to enhance the performance of an ALNS-based algorithm. A metaheuristic algorithm with a single solution vector, such as ALNS, is commonly constructed with two main phases: (i) a construction of an initial solution and (ii) an iterative exploration of the neighborhood to optimize the solution quality. Nevertheless, our review shows that a handful of works have proven that an additional post-optimization phase can improve the quality of solution provided by the second phase. The effectiveness of such strategy has long been known in the research community of memetic computing (see Neri and Cotta, 2012), in which the results of the optimization process with genetic operators (crossover and mutation) are improved with local search operators. During the design process of ALNS-based algorithm, this post-optimization phase can be implemented whether using an exact method (Muller et al., 2012, Pereira et al., 2015, Wen et al., 2016, Keskin and Çatay, 2018, Koc et al., 2018; Canca et al., 2019, Keskin et al., 2019, Koç et al., 2019, Vareias et al., 2019, Zhao and Lu, 2019, Shao and Dessouky, 2020) or a local search procedure, such as the variable neighborhood descent (Avci and Avci, 2019; Graf, 2020; Pan et al., 2021).
- As seen in Table 9, a reasonable amount of ALNS literature considered hybridizing the ALNS with other frameworks and have shown promising results. However, there is still no conclusive result on which metaheuristic framework works best when implemented along with ALNS, as the majority of reviewed articles still implemented ALNS using the original structure proposed in Ropke and Pisinger (2006a; 2006b), where the ALNS is embedded into SA framework. In this regard, the research community of ALNS could attempt to answer this issue in the future.

5.2. Overview of ALNS application

Moving on, this subsection presents the application aspect of ALNS based on the results of our review. We first discuss in Subsection 5.3.1 the different classes of the optimization problem in which the ALNS-based heuristic is implemented. We then continue the discussion with a broad overview of the application areas of ALNS in Subsection 5.3.2.

5.2.1. Class of optimization

We start the discussion by providing some basic explanations on the aspects of the optimization problem reviewed in this study. We followed some of the general classifications of optimization problems from Sarker and Newton (2007), in which they classified optimization problems according to four interconnected levels: (i) the objective classification – *single vs. multiple objectives*, (ii) the problem classification – *unconstrained vs. constrained,* (iii) the variable classification – *continuous vs. discrete vs. mixed,* and (iv) the function classification – *linear vs. non-linear, convex vs. nonconvex, differentiable vs. nondifferentiable*. In this study, we did not consider the problem classification since we observed that the current implementations of metaheuristic algorithms were generally for constrained problems. We also did not consider the function classification since our focus on this study is more on the heuristic algorithm, which is generally introduced as a solution for the scalability issue of a mathematical programming method. Therefore, we only took the objective and variable classifications (search space) into account. We then added another aspect of the state of input parameters – *deterministic vs. stochastic vs. mixed*, which arguably becomes another critical issue in the research community of operations research.

Fig. 4 presents the results of our review process. In terms of the number of objective functions, we observed that the majority of studies on ALNS (242 papers, 96.80%) still focused on the implementation of the ALNS-based heuristic to solve a single-objective optimization problem. Contrarily, there were only eight studies (3.20%) from Buer and Kopfer (2014), Rifai et al. (2016), Cota et al. (2019), Ji et al. (2019a), Liao et al. (2020), Liu and Liao (2021), Al Chami et al. (2021), and Rifai et al. (2021) which applied ALNS-based heuristic for MOOPs. The study from Rifai et al. (2016) can be considered to be the first study to formalize the multi-objective extension of ALNS metaheuristic, namely the multi-objective ALNS, which was implemented to solve the distributed reentrant permutation flow shop scheduling. Additionally, several studies also considered multiple objectives but not in a conflicting fashion, such as the study from Demir et al. (2014) in the bi-objective pollution-routing problem. However, we observed that these studies transformed those multiple objectives into a single-objective problem, and we chose to stick with the property of multi-objective optimization

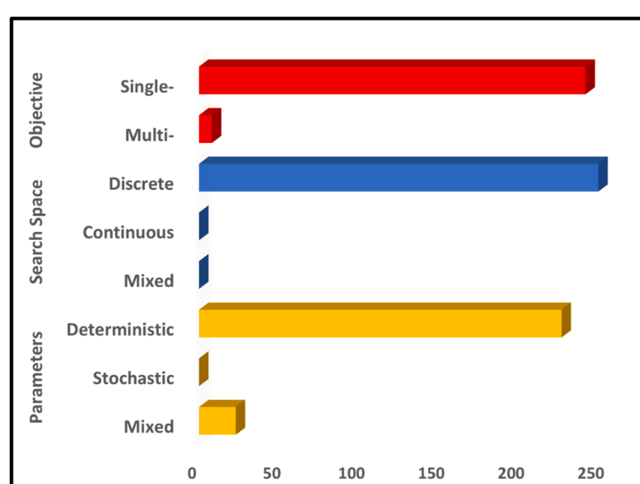

Fig. 4. Overview of class of optimization.

described by Deb et al. (2008) that in a multi-objective optimization task, "*there are two distinct goals of optimization, instead of one*." Therefore, we classified these studies as a single-objective optimization.

In terms of the search space, we observed that all the reviewed studies implemented the ALNS to the class of discrete optimization problems. This finding is not surprising due to the nature of ALNS as a metaheuristic for combinatorial optimization problems (Ropke and Pisinger 2006a; 2006b). We also need to clarify that we are aware of several studies that implemented their ALNS-based algorithms to solve a combinatorial optimization problem which involves several continuous decision variables, such as the presence of continuous variables to decide the arrival time of vehicles at a certain customer node in the routing problems with time windows (see Ropke and Pisinger, 2006b; Goeke and Schneider, 2015; Lee and Kim, 2015). However, it should be noted that the actual search space of the algorithm comprises the sequence of visits, and the values of these continuous variables are generally decided by the visit sequence.

Lastly, we also observed that most studies of ALNS (227 studies, 90.80%) still focused on the class of deterministic optimization problem, in which the values of all problem parameters were known in certainty. While unsurprisingly there was no study in a pure stochastic optimization problem, a handful of studies (23 studies, 9.20%) considered the presence of one or more uncertain parameters (Laporte et al., 2010; Lei et al., 2012; Chen et al., 2014; Nolz et al., 2014; Taş et al., 2014; Chaharsooghi et al., 2016; Ghilas et al., 2016a; Hasani and Khosrojerdi, 2016; Li et al., 2016b; Li et al., 2016c; Luo et al., 2016; Majidi et al., 2017; Kisialiou et al., 2018a; Momayezi et al., 2021; Schiffer and Walther, 2018b; Zhu and Sheu, 2018; Kisialiou et al., 2019; Vareias et al., 2019; Issabakhsh et al., 2021; Markov et al., 2020; Mourad et al., 2021; Nasri et al., 2020; Zhang et al., 2020; Keskin et al., 2021). Some examples of those parameters are the waiting time and service time of each node (Chen et al., 2014; Kisialiou et al., 2018a; Issabakhsh et al., 2021; Nasri et al., 2020; Zhang et al., 2020; Keskin et al., 2021), the travel time between nodes (Chen et al., 2014; Taş et al., 2014; Li et al., 2016c; Kisialiou et al., 2018a; Vareias et al., 2019; Nasri et al., 2020; Zhang et al., 2020), the demand of the nodes (Laporte et al., 2010; Lei et al., 2012; Nolz et al., 2014; Ghilas et al., 2016a; Hasani and Khosrojerdi, 2016; Luo et al., 2016; Majidi et al., 2017; Schiffer and Walther, 2018b; Zhu and Sheu, 2018; Kisialiou et al., 2019; Markov et al., 2020; Mourad et al., 2021), and the possibility of disruption on the facilities (Chaharsooghi et al., 2016; Hasani and Khosrojerdi, 2016; Momayezi et al., 2021).

Overall, as for the class of optimization, we obtain the following insights:

- Most of the reviewed studies still implemented ALNS on a single-objective, deterministic, and discrete optimization problem. However, we noted that a handful of studies have extended their focus to the issue of optimization under uncertainty. Several studies have also discussed the applicability of ALNS in solving MOOPs. These facts imply that ALNS has been considered by the designer of optimization algorithms in solving complex optimization problems which comprise various realistic forms of problem extension.
- In handling the uncertainty issue with ALNS, various approaches have been implemented by researchers. We observe that ALNS-based heuristics have been integrated with stochastic programming (Laporte et al., 2010; Lei et al., 2012; Chen et al., 2014; Nolz et al., 2014; Taş et al., 2014; Chaharsooghi et al., 2016; Ghilas et al., 2016a; Li et al., 2016c; Luo et al., 2016; Momayezi et al., 2021; Zhu and Sheu, 2018; Vareias et al., 2019; Markov et al., 2020; Mourad et al., 2021), fuzzy optimization (Majidi et al., 2017; Zhang et al., 2020), simulation–optimization (Kisialiou et al., 2018a; Kisialiou et al., 2019; Nasri et al., 2020; Keskin et al., 2021), and robust optimization (Hasani and Khosrojerdi, 2016; Schiffer and Walther, 2018b; Issabakhsh et al., 2021). This shows the flexibility of ALNS in solving optimization problems under uncertainty and we predict that more studies will attempt to implement ALNS in this topic due to the proven effectiveness of ALNS in solving deterministic optimization problems.

5.2.2. Areas of application

Next, we attempted to classify the 252 reviewed studies based on the areas where the ALNS-based heuristic was implemented. These studies were classified into several categories based on the domain of the implementation. Fig. 5 then presents the overview of the results. It should be noted, however, that a case study can be classified into more than one category. Readers are invited to check the Electronic Appendix to see the complete classification results.

As seen in Fig. 5, most of the implementations of the ALNS-based heuristic were concentrated on two classical problems in operations research: routing (186 papers) and scheduling (141 papers). This finding is not surprising since the early studies on ALNS were dedicated to the class of vehicle routing problems (Ropke and Pisinger, 2006a; Ropke and Pisinger, 2006b; Pisinger and Ropke, 2007), workforce scheduling (Cordeau et al., 2010), and machine scheduling (Wang et al., 2012). In addition, we observe a wide range of problem classes where ALNS-based algorithms were implemented to solve routing problems, ranging from the VRP with time windows (Lee and Prabhu, 2016; Ben Ticha et al., 2019; François et al., 2019; Liu et al., 2019b; Vareias et al., 2019; Nasri et al., 2020; Yu et al., 2020; Li et al., 2021b; Chen et al., 2021), VRP with backhauls (Ropke and Pisinger, 2006a; Koch et al., 2018), location-routing problem (LRP) (Contardo et al., 2012; Yang and Sun, 2015; Koç et al., 2016a; Koç et al., 2016b; Schiffer and Walther, 2018a; Schiffer and Walther, 2018b; Schiffer et al., 2018; Koç, 2019; Sun et al., 2019b; Theeraviriya et al., 2019; Theeraviriya et al., 2020; Şatir Akpunar and Akpinar, 2021), periodic LRP (Koç, 2016; Tunalioğlu et al., 2016), arc routing problem (Laporte et al., 2010; Salazar-Aguilar et al., 2013; Chen et al., 2014; Riquelme-Rodríguez et al., 2016; Riquelme-Rodríguez et al., 2014; Mofid-Nakhaee and Barzinpour, 2019; Khajepour et al., 2020), pickup-and-delivery (PDP) problem (Qu and Bard, 2012; Masson et al., 2013; Qu and Bard, 2013; Grimault et al., 2017; Majidi et al., 2018; Zhu and Sheu, 2018; Bruglieri et al., 2019; Hof and Schneider, 2019; Sun et al., 2019a; Hornstra et al., 2020; Al Chami et al., 2021; Chang et al., 2021), and PDP with time windows (Ropke and Pisinger, 2006b; Cherkesly et al., 2015; Lee and Kim, 2015; Ghilas et al., 2016a; Ghilas et al., 2016b; Li et al., 2016a; Naccache et al., 2018; Sun et al., 2020; Mourad et al., 2021). We invite readers to check the Electronic Appendix, in which we have presented a complete mapping of the ALNS studies on routing and scheduling problems. Moreover, we also observed that ALNS-based heuristics have often been implemented to solve another popular class of problems in operations research, namely the locational analysis where we found 22 studies working on this topic. These 22 studies ranged from a pure locational analysis (see Pereira et al., 2015; Guo et al., 2018; Momayezi et al., 2021) to the integration between the analysis of location and routing aspects (see Contardo et al., 2012; Schiffer and Walther, 2018a; 2018b) in the form of location-routing problem (see Drexl and Schneider, 2015; Mara et al., 2021).

From the review in Fig. 5 and Electronic Appendix, we can observe several trends that emerged within the context of application of ALNS, as follows:

- The ALNS has been implemented in various extensions of routing, scheduling, and locational problems. These problems are generally considered as the classical problems in operations research, in which ALNS-based algorithms have been proven by numerous studies as an effective solver. This finding indicates the establishment of ALNS as a new popular metaheuristic framework that may be considered as a top priority by algorithm designer when facing and solving a complex optimization problem.
- We find numerous ALNS implementations in several classical industrial domains (see Fig. 5), such as manufacturing and production systems (31 studies), maritime logistics (20 studies), agriculture (12

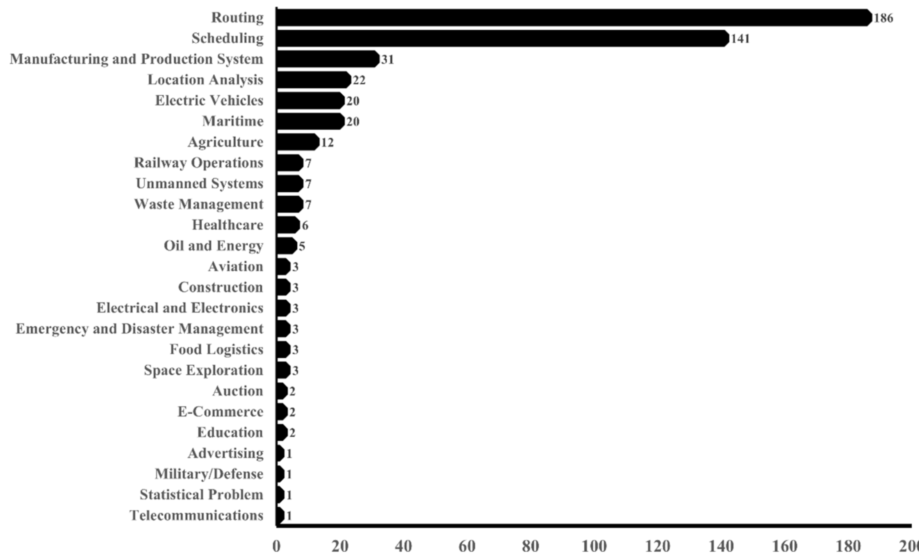

Fig. 5. Overview of application areas.

studies), railway operations (7 studies), healthcare (6 studies), and waste management (7 studies). We also find several ALNS implementations in some contemporary domains, such as electric vehicles (23 studies) and unmanned systems (7 studies). This indicates the flexibility and suitability of ALNS, as a neighborhood-based metaheuristic, to solve various forms of optimization problems.

6. Suggestions for future research

In this section, some potential directions for future research on ALNS are presented based on the reviewed literature and the emerging trends of ALNS research. The discussion of future research directions is divided into two parts, the algorithm developments (Subsection 6.1) and ALNS applications (Subsection 6.2).

6.1. Algorithm developments

- Formal guideline on selecting the right destroy-repair operators.

As a local-search-based metaheuristic, it is easily observed that the epitome of the ALNS framework is an iterative implementation of selected destroy and repair operators for exploring the search space. The seminal work of Pisinger and Ropke (2007) argued that this portable approach has been the main advantage of ALNS as it provides flexibility in designing ALNS for numerous applications. Several destroy operators (e.g. random, worst, Shaw, history-based, neighborhood, and cluster removals) and repair operators (e.g. greedy, k-regret, random, sequential, shaw, and cluster insertions) described in Table 8 can be adopted as general operators in the ALNS, as their mechanisms are not bounded to problem-specific characteristics. Additionally, previous knowledge on several well-performing problem-specific heuristics can also be inserted into the framework. This feature is supported by Pisinger and Ropke (2019) who mentioned that, based on their experience, the insertion of more (reasonable number of) neighborhoods into an ALNS-based heuristic usually leads to better performance of the heuristic.

Nevertheless, from the taxonomical review, we observe that this flexible paradigm leads to a drawback of the presence of overly tuned ALNS-based heuristics with a large number of operators. From practical point of view, this trend reduces the ability of the algorithms to be reproduced, thus restricting the accessibility of ALNS-based algorithms for non-expert users who value robustness and the ease of development (Sörensen et al., 2018). We argue that such situation happens because there is currently no general consensus on how to design the right sets of destroy and repair operators.

Therefore, the ALNS research community can fill this gap by conducting research on the development of formal guideline to select the destroy-repair operators. One excellent example is from Schiffer and Walther (2018a), who proposed a multi-phase procedure that may serve as a promising alternative. The notion of their proposal is to eliminate destroy-repair operators that do not lead to better solutions in terms of objective value from the final version of ALNS before its implementation. Additionally, the *meta*-analysis studies from Santini et al. (2018) and Turkeš et al. (2020), who respectively discussed the impact of different acceptance criteria and the adaptive layer of ALNS, can be a very good starting point for the future ALNS development.

- Parameter-less ALNS.

The standard form of ALNS from Ropke and Pisinger (2006a; 2006b) is embedded in the SA framework as the master level framework. Generally, SA is known as a metaheuristic framework that employs a handful of parameters which are needed to be carefully tuned before its deployment, such as the starting temperature T_0, cooling rate α, and other parameters related to the stopping criterion used (e.g., number of maximum iterations, end temperature). On the other hand, the use of several destroy-repair operators and the weight adjustment for the adaptive selections of those operators also lead to the addition of several problem-specific parameters. Consequently, one can easily see that the implementation of ALNS requires the designer to tune a quite large number of parameters.

This parameter tuning process is widely known to be a crucial step in designing a well-performing metaheuristic for the given problem. Nevertheless, although several formal procedures of parameter tuning do exist, such as F-race (Birattari et al., 2002), iRace (López-Ibánez et al., 2016), and ParamILS (Hutter et al., 2009), the task of parameter tuning has long been known as a complex and resource-consuming task (Montero et al., 2014). One of the fastest ways to decide the value of certain parameters is perhaps to borrow the corresponding value implemented in previous literature. However, the designer of the algorithm must also note that the best value for the parameter set highly depends on the characteristics of problem on hand (Montero et al., 2014). In addition, the tuning process of algorithm parameters usually requires the designer to execute many runs of the algorithm using a set of different problem instances. Therefore, this process might incur more resources than the intended task itself. In this regard, we observe that a proposal on the innovative way of reducing the number of parameters in

ALNS will be a meaningful practical contribution.

- ALNS-based matheuristic.

Our review suggests that the classical ALNS is often hybridized by researchers with several different techniques to improve its performance. Among those efforts, we observe one interesting direction that is aligned with the current trends in heuristic research: the integration of ALNS with a mathematical programming model as a matheuristic algorithm. The popularity of matheuristic algorithm has been rising recently due to the numerous documentations of the effectiveness of this approach, as implied in the survey from Archetti and Speranza (2014) who reviewed the implementation of matheuristic approach in routing problems. Within the context of ALNS, we have seen that the flexible structure of the ALNS framework has led to several creative implementations of ALNS-based matheuristic algorithm, in which the corresponding exact method can be embedded as (1) an initialization procedure (e.g. Mancini et al., 2016; Ghiami et al., 2019; Rohmer et al., 2019), (2) post-optimization procedure (e.g. Muller et al., 2012; Pereira et al., 2015; Keskin et al., 2019; Shao and Dessouky, 2020), or even as (3) a repair operator of ALNS (e.g. Katterbauer et al., 2012; Guastaroba et al., 2020; Hà et al., 2020). Considering the flexible structure of ALNS and the evidence of the effectiveness of this class of approach, we expect the popularity of ALNS-based matheuristic approach will increase in the future. Moreover, we refer the interested readers to this excellent review from Ball (2011) who provided the basic theoretical properties of developing a mathematical programming-based heuristic.

6.2. ALNS applications

- More studies on the multi-objective ALNS.

Our taxonomical review has shown that there are several works which have discussed the application of ALNS in optimization problems with multiple objectives (Buer and Kopfer, 2014; Rifai et al., 2016; Cota et al., 2019; Ji et al., 2019a; Liao et al., 2020; Liu and Liao, 2021; Al Chami et al., 2021; Rifai et al., 2021). However, we are convinced that the attention of the ALNS research community to the MOOPs is still lacking and could still be extended more.

The presence of multiple objectives in optimization problems is one of important topics in operations research (Laszczyk and Myszkowski, 2019). From the practical perspective, in a real-world setting, it is natural for the decision-maker to consider more than one objective which are potentially conflicting with each other and increasing the complexity of the decision-making process (Deb, 2008). As a result, research on the development of algorithm for MOOPs usually focuses on the effort to obtain a representative Pareto-optimal frontier which comprises multiple solutions, instead of a single optimal solution. This Pareto-optimal frontier would serve as an input for the subsequent steps to select a single applicable solution that satisfies the preference of the decision-maker.

To evaluate the quality of the Pareto-optimal frontier, two key aspects need to be measured, namely the convergence and diversity of the solution (Laszczyk and Myszkowski, 2019). In this regard, a particular challenge to implement ALNS in multi-objective optimization arises from the fact that ALNS belongs to the class of trajectory search algorithm, where a single solution vector is continuously updated and evaluated. On the other hand, the requirement to obtain multiple Pareto-optimal solutions with good diversity measurement clearly favors the class of population-based methods. In fact, some of the most popular algorithms in MOOP belong to the population-based class, such as the Non-dominated Sorting Genetic Algorithm-II (Deb et al., 2002) and Multi-objective Particle Swarm Optimization (Coello and Lechuga, 2002). Therefore, we conclude that exploring the effectiveness of ALNS-based algorithms in MOOPs could be an interesting contribution for future research.

- Proposals of ALNS as a unified solution for a class of optimization problems outside of vehicle routings.

The development of a unified heuristic for a class of optimization problems is known as a crucial step towards the generalization of a proven well-performing heuristic algorithm as a general solver for the corresponding class of problems. This kind of general solver, which can solve multiple problem variants effectively, is needed and most suitable to be implemented in the real-life environment since the transportation needs of different companies are often different (Pisinger and Ropke, 2007) and the development of several problem-specific heuristic algorithms for several problem variants would surely need more resources. Through this study, we observe that there are several studies that developed a unified heuristic algorithm based on ALNS. Ropke and Pisinger (2006a) developed a general heuristic for a class of variants of vehicle routing problems with backhauls, while Pisinger and Ropke (2007) proposed an ALNS-based heuristic to solve a large class of vehicle routing problems. More recently, Koç (2016) proposed a unified ALNS to solve a class of periodic location routing problems. While these research works have shown the suitability of ALNS to be a framework for a unified heuristic, their implementations are still concentrated in the field of vehicle routing. Thus, by looking at the number of various application areas of ALNS, one may consider developing a general-purpose ALNS to solve a class of problem variants from other application areas where the effectiveness of ALNS-based heuristics has been evidently proven, such as the scheduling problems and facility location problems (see Fig. 5).

- Tackling optimization problems under uncertainty with ALNS.

From our review on the class of optimization, we observe that a considerable attention has been given to the implementation of ALNS to solve optimization problems with a stochasticity issue. Nevertheless, we expect that more research will present a meaningful contribution in this issue.

From practical perspective, the consideration of uncertainty has been a major issue in the design process of a system since the presence of randomness in real-life data is often unavoidable (Gorissen et al., 2015). As an illustration, within the design process of a logistics system, some problem parameters naturally contain a degree of stochasticity and cannot be exactly estimated, such as the demand of customers (e.g. Laporte et al., 2010; Lei et al., 2012), the travel time of vehicles (e.g. Vareias et al., 2019), and the time required to serve the customer nodes (e.g. Nasri et al., 2020). Such uncertainty can also rise from the occurrence of sudden events, like accidents, which in turn disrupt the system and might diminish the quality of the current 'optimal solution' implemented on the system.

Given the occurrence of the recent COVID-19 pandemic which disrupted the majority of global supply chain network (Nikolopoulos et al., 2021), we predict that the research community in operations research will put more focus on the development of a robust and reliable solution for a given optimization problem. In addition, looking at how the effectiveness of ALNS has been widely proven in solving optimization problems with deterministic data, proposing ALNS-based algorithms for tackling optimization problems under uncertainty could be an interesting direction to pursue. In this regard, we note that some major techniques are available to extend ALNS-based heuristics in dealing with optimization problems under uncertainty, such as stochastic programming (Birge and Louveaux, 2011), fuzzy programming (Luhandjula, 2015), robust optimization (Gorissen et al., 2015), and simulation–optimization or also known as simheuristics (Juan et al., 2015).

- Implementing ALNS in humanitarian domains.

As implied in Fig. 5, research community has proven the effectiveness of ALNS in a wide range of application areas. Whilst two of the most popular application areas for ALNS implementation insofar are vehicle routing and scheduling, we also observe that the ALNS research community is very active in several popular areas in operations research, such as location analysis, electric vehicles, maritime logistics, and manufacturing and production system. In retrospect, this observation implies the flexibility of ALNS to be implemented in various domains. As such, we hope that the research community should make more attempt to implement ALNS-based heuristics for solving optimization problems in humanitarian domains, such as emergency and disaster management (Faharani et al., 2020), healthcare (Rais and Viana, 2011), and blood logistics (Pirabán et al., 2019).

Based on the observation of Fig. 5, ALNS studies in those mentioned domains remain scarce. Operational problems addressed in humanitarian domains tend to be highly complex and challenging. For instance, the logistics processes of blood products constitute to a time-constrained distribution of perishable products (Pirabán et al., 2019), while similarly, the operational tasks in post-disaster response are naturally executed under tight time constraint and hazardous environments (Faharani et al., 2020). Considering the potential of ALNS in solving numerous highly complex optimization problems, implementing ALNS in humanitarian domains might be a meaningful research gap, as contributions on optimizing those domains can provide a huge impact to the welfare of the society, such as reducing the soaring costs of healthcare services and/or saving human lives.

7. Concluding remarks

In the previous sections, we have reviewed the state-of-the-art of ALNS research. We present a timely review of the ALNS algorithm and its applications. Our study classifies the progress of ALNS research based on a simple taxonomy of 252 SCOPUS-indexed articles published from 2006 to 2021. The results of these classification attempts are presented in a spreadsheet-based table which can be downloaded as an Electronic Appendix.

From this study, we can draw several interesting insights on the ALNS research progress to answer our research questions. In terms of the intensity of publications related to ALNS, our analysis in Section 4 has shown that there has been an escalating trend of ALNS-related articles. Our review in the application areas of ALNS (Fig. 5) also has shown that ALNS-based algorithms have been implemented in various domains, which highlight the flexibility of this algorithm. In essence, these facts confirm the establishment of ALNS as a new popular metaheuristic framework. Moving on, the taxonomical review in Section 5 has shown that research on ALNS algorithm has been extended in several directions. From there, we remark several emerging trends. In terms of the technical development of ALNS itself, we note that two works from Turkeš et al. (2020) and Santini et al. (2018) have respectively attempted to highlight the impact of the adaptive mechanism and acceptance criterion of the ALNS framework, indicating that the research community on ALNS has begun to move into the 'scientific' era of metaheuristics (Sörensen et al., 2018). Next, in terms of the hybridization of ALNS with other methods, we reveal an exciting trend on the integration of ALNS with exact methods which forms an ALNS-based matheuristic. We also observe other efforts to improve the performance of ALNS by integrating a local search procedure or another well-known metaheuristic. Furthermore, our review on the class of optimization of ALNS (Fig. 4) reveals that most studies implemented ALNS on a single-objective, deterministic, and discrete optimization problem. Meanwhile, in terms of the domain areas where ALNS has been implemented, we find numerous ALNS implementations across a range of classical domains, such as manufacturing and production systems, maritime logistics, agriculture, railway operations, healthcare, and waste management. Additionally, ALNS has also been implemented in some contemporary domains, such as electric vehicles and unmanned systems. Finally, in Section 6, we concluded our study by discussing some potential directions for the future research on ALNS.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cor.2022.105903.

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