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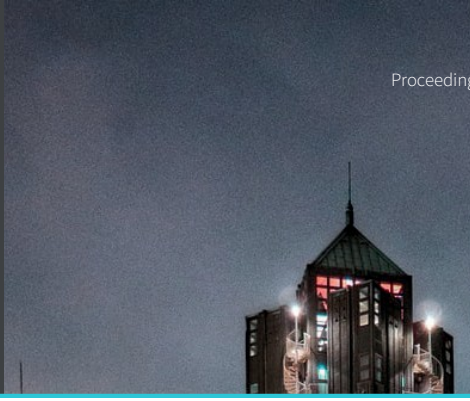

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Simulation-based Optimization at Container Terminals: A Literature Review

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Purpose: While simulation-based optimization has been discussed in theory and practically employed at container terminals, the different publications in this field have not yet been presented and compared in a structured manner. This paper gathers the latest developments and examine the similarities and differences of the provided approaches. Furthermore, research gaps are identified.

Methodology: The recent literature of simulation-based optimization on container terminals is examined using a mapping review approach. Emphasis is laid on the covered problems, chosen meta-heuristics, and the shapes of the solution space.

Findings: In the applied literature of container terminals genetic algorithms prevail, both for scheduling problems and for the determination of discrete and/or continuous parameters. Because of the no-free-lunch-theorem for optimization, it is open whether the chosen optimization approach serves the purpose best.

Originality: To the best of our knowledge, the existing literature regarding simulation-based optimization at container terminals has never been addressed in a detailed overview. The elaborated comparison of the different publications leads to further research directions

Keywords: Simulation-based Optimization, Simulation-based Optimisation, Container Terminal, Maritime Logistics

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1 Introduction

In globe-spanning supply chains, maritime container terminals are of major importance. In terms of volume, over 80% of the world merchandise trade is handled by ports while in 2017 17.1% of global trade volumes were containerized (UNCTAD 2018). Container terminals need to run smoothly and cost-efficiently both for the economy depending on the transported goods and the terminal owners to stay in competition. Therefore, container terminal operations have been an active field of research for a long time (Steenken, Voß & Stahlbock 2004; Gharehgozli, Roy & DeKoster 2016). One major obstacle the authors present is that container terminals differ from each other in their terminal layout, the employed equipment, and the level of automation and digitalization, to name a few. This increases the difficulty to generalize insights of case studies and to transfer solutions and best practices between container terminals. On the other hand, container terminals will need to change and learn from the success stories of others in order to stay competitive. A continued market concentration in liner shipping allows shipping alliances to exert high pressure on container terminals (UNCTAD 2018).

The sheer complexity of a container terminal as well as the lack of generalizability for results obtained from a specific field study make it necessary to limit oneself on certain aspects. Some study fields have been of special interest, such as the Berth Allocation Problem (BAP), the Quay Crane Assignment Problem (QCAP), or the Quay Crane Scheduling Problem (QCSP) (Stahlbock & Voß 2007). Bierwirth & Meisel (2010) show that in literature there are use-case-specific assumptions, like spatial con-straints (discrete,

continuous or hybrid berth layout), knowledge about arrival times in advance, whether ships have a strict time schedule etc. Furthermore, while some publications focus on a single problem (Dai et al. 2008), others perceive this as too narrow and formulate an integrated problem consisting of several parts (cf. Liang, Huang & Yang 2009). Many of these problems have been shown to be NP-hard, which is a major challenge (Steenken et al. 2004). While exhaustive search is theoretically possible, in many areas it has shown to be too time-consuming for practical appli-cation (Woeginger 2003). Hence, for real-world applications approximations need to suffice (Bierwirth & Meisel 2015).

Among others, sufficiently good input parameters can be estimated by using simulation-based optimization. For the same problem, different optimization algorithms can be used. This leads to the underlying question of this paper: Which algorithm(s) lead(s) to the best results under limited resources? In the following section, first more background on simulation-based optimization and related work is provided. In Section 3, the methodology is described. The results are presented and discussed in Section 4. Finally, in Section 5 conclusions are drawn.

2 Background and Related Work

The term "simulation-based optimization" is the key concept of this publication. Depending on the publication, different definitions or informal descriptions are used for the same term. In the following, first a definition for simulation-based optimization is provided. Afterwards, previous related publications are presented.

2.1 Simulation-based Optimization

Zhou et al. (2018) define simulation-based optimization as a method "to evaluate the performance of the system for a given configuration, while the optimization algorithm explores alternative configurations in the solution space and identifies the optimal setting". In this publication this definition is narrowed: Simulation-based optimization is a procedure to examine the most promising subset of all available solutions, i.e. parameter configurations. Therefore, multifidelity approaches such as presented by Li et al. (2017) are out of focus. To evaluate a specific parameter configuration, it is entered into a system which imitates (parts of) the container terminal. Such a system can be e.g. self-written code, or simulation software. For this publication it needs to meet the general definition of simulation as a "[r]epresentation of a system with its dynamic processes in an experimentable model to reach findings which are transferable to reality; in particular, the processes are developed over time." (Verein Deutscher Ingenieure 2014). Furthermore, simulation models can incorporate randomness to reflect the stochasticity of the real-world system. This surpasses simple deterministic evaluation schemes which can be evaluated within split-seconds.

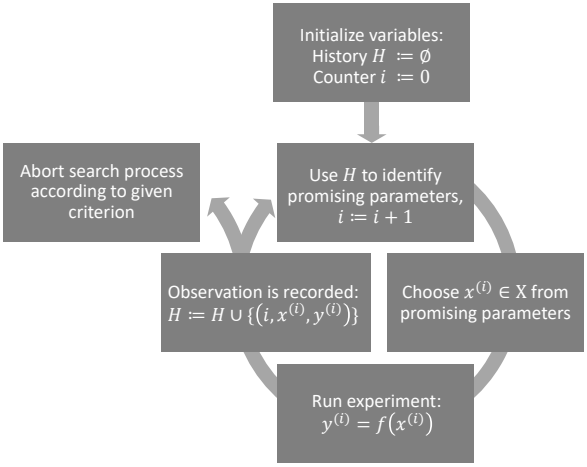

Figure 1: The cycle of simulation and optimization for simulation-based optimization

The concept of simulation-based optimization goes by different names, such as Simulation Evaluation (Figueira & Almada-Lobo 2014), Simulation Optimization (Amaran et al. 2016) or Optimization via Simulation (Xie, Frazier & Chick 2016). The integral assumption is that the system (here: container terminal) is too complex to directly apply mathematical programming methods. Stochasticity and interaction of the different subsystems hinder the observer to predict the impact of certain parameter configurations. The container terminal is assumed to be so complex that directly examining internal processes are fruitless.

Simulation-based optimization belongs to the larger family of black-box optimization procedures which are also referred to as meta-heuristics (Chopard & Tomassini 2018) or derivative-free optimization procedures

(Rios & Sahinidis 2013). Meta-heuristics are characterized by their universality. They can be used in many different disciplines for optimization, e.g. Simulated Annealing (SA) has been used for vehicle routing (Yu et al. 2017), job shop scheduling (van Laarhoven, Aarts & Lenstra 1992), or to define genetic structures of populations (Dupanloup, Schneider & Excoffier 2002).
A visualization of the concept simulation-based optimization can be seen in Figure . During the ongoing search process, in the history H the so far obtained observations are gathered. They guide the search by identifying promising parameters $\{x\}$, of which one, $x^{(i)}$, is chosen for a simulation experiment. The observed result $y^{(i)}$ is recorded and can be used to further guide the search. Usually meta-heuristics are formulated in a way that a stopping criterion needs to be explicitly defined. This can be defined e.g. by time, by number of cycles, the (lack of) obtained improvement within the last k evaluations.
The algorithmic steps to define a metaheuristic are by definition generic so that it can applied to new cases. Wolpert & Macready (1997) show that a metaheuristic which exploits the underlying structure of a certain optimization problem very well, leads to results worse than random results for another optimization problem. In other words, a meta-heuristic which picks the right next parameter configuration for every optimization problem can't exist. Still, empirical work can show that a certain meta-heuristic exploits the underlying structure of a specific problem better than another. This makes it inevitable to use large datasets, if available benchmarks, as well as reported results in comparable literature.

2.2 Related Work

A plethora of literature reviews deal with metaheuristics. Some, like Xu et al. (2015), used maritime logistics as a use case for showing the applicability of more general concepts. They present different optimization approaches, i.e. ranking and selection, black-box search methods that directly work with the simulation estimates of objective values, meta-model-based methods, gradient-based methods, sample path optimization, and stochastic constraint and multi-objective simulation optimization. For container terminals, recently only a subset of these options has been applied.

Zhou et al. (2018) reviewed different ways of how simulation and optimization had been jointly used in the field of maritime logistics. That included optimization tasks regarding the landside and waterside of the container terminal as well as the scheduling of vessels from the perspective of a ship owner. Based on the gathered literature, they differentiate between several modes, i.e. simulation-supported optimization, simulation optimization iteration, optimization-embedded simulation, and simulation-based optimization. The latter category is elaborated on in this publication.

Bierwirth & Meisel (2015) present the literature related to seaside operations planning. They focus on BAP, QCAP and QCSP and options of how to integrate them. A detailed problem classification for each of the problems provides an overview of past work in this field. Tactical planning is out of their scope and they do not examine the employed methodology, i.e. which algorithm has been used to search through which kind of solution space.

Several more general literature overviews about container terminals exist (Steenken et al. 2004; Stahlbock & Voß 2007; Carlo, Vis & Roodbergen 2014b, 2014a; Gharehgozli, Roy & DeKoster 2014, 2016; Dragović, Tzannatos & Park 2017).

Previous literature reviews follow two threads: Either the subject of simulation-based optimization is approached on a methodological level, then practical aspects of the container terminals often are less of concern. Or the subject is approached from a problem-based perspective and the employed methods are out of focus. This paper brings these threads together in order to create a new perspective.

3 Methodology

According to the literature review typology of Grant & Booth (2013), the following review is referred to as a mapping review. It targets at categorizing the existing literature about simulation-based optimization at container terminals. The focus of this study is to investigate which aspects of the container terminal have been optimized with simulation-based optimization, which search algorithms have been used, and how the shape of the solution space looks like. The latter can indicate which algorithms could serve as alternatives. Grant & Booth (2013) argue that mapping reviews are an appropriate tool for gaining an overview and identifying research gaps.

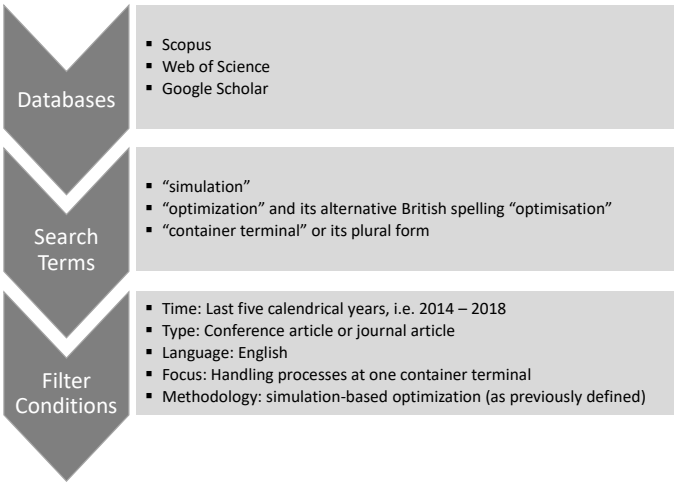

Figure 2: The process of searching the literature

The literature search process can be seen in Figure 2. Scopus, Web of Science, and Google Scholar are used to obtain the literature of interest. This review aims at covering a wide range of recent publications so that rare approaches are covered as well. The search terms to identify simulation-based optimization are "simulation", and "optimization" (alternatively in British English "optimisation"). This ensures that all the different terms for the same concept (as described in Section 2.1) are covered. Furthermore, the term "container terminal" (or "container terminals") needs to be mentioned in the publication. The search has been restricted to published conference articles and journal articles. The time range of interest is limited to the last five calendrical years, i.e. 2014 - 2018. Newer publications are ignored for the sake of repeatability. Each of the found articles needs to match the following criteria: (1) the publication is in English, (2) the scope

of the examined system is restricted to one or several problems at one container terminal, (3) the examined problem solely examines the characteristics of the handling processes, and (4) the authors optimized one aspect of the container terminal, and (5) they used simulation-based optimization as previously defined for optimization.
The obtained literature is presented in a categorized manner in order to increase the comprehensibility. The distinction is based on the structure of the solution space and leads to two groups: (1) permutation space, or (2) an n-dimensional discrete or continuous space.

3.1 Permutation Space

For a set with k distinct items, k! permutations exist. The most common observed problem is to decide about in which order a set of tasks will be executed. In most cases, the permutation space can be restricted as constraints exist, such as dependencies between tasks. Still, with a growing size of the set, the solution space quickly turns intractable. At container terminals, plenty of well-examined scheduling problems exist (Steenken et al. 2004; Stahlbock & Voß 2007; Bierwirth & Meisel 2010, 2015; Gharehgozli et al. 2016). A set of resources of the same type, such as Quay Cranes (QC), Yard Trucks (YT), or Yard Cranes (YC), needs to be assigned to transport containers from a source to a destination. The major difficulty lies in determining which machine is paired with which task. These scheduling problems suffer from exactly that explosion of the solution space which is one of the reasons for a mostly sub-optimal employment of equipment at container terminals.
On a methodological level, the scheduling problems for the different types of equipment (i.e. QCSP, YCSP, and Vehicle Dispatching Problem (VDP))

share many characteristics. Hartmann (2004) defines a general scheduling model to "consist of the assignment of jobs to resources and the temporal arrangement of the jobs subject to precedence constraints and sequence-dependent setup times". The model is later applied to assign straddle carriers, automated guided vehicles, and stacking cranes to transportation tasks, as well as workers to jobs related to the maintenance of reefer containers. This encourages the perspective that the different scheduling problems can be compared on a methodological level, and approaches which have been applied for one scheduling problem might also be used for another.

3.2 n-dimensional Discrete and/or Continuous Space

When a researcher or practitioner is asked to optimize a container terminal without further constraints, plenty of alternatives exist. With each questioned design decision, the solution space grows exponentially. For the simple case of choosing between two levels for each considered factor (e.g. different strategies for each equipment type), for n different factors 2^n possible solutions exist. With an increasing amount of levels, this amount further increases. This makes the execution of a grid search quickly intractable. The choice of the most promising subset of the solution space is difficult because of the complex interactions of the different subsystems at a container terminal.

When planning the extension or modification of a terminal, different facets of a terminal are of interest. Often the effect of changes in the berth layout, yard layout, and gate and rail area layout on the behavior of the container terminal is of interest (Leriche et al. 2016; Kotachi et al. 2018). As a change

in one of them influences the performance of the others, the subset to evaluate must be chosen with care. Furthermore, the amount of equipment to purchase increases the levels to investigate and hence the size of the solution space tremendously. The solution space can be limited by examining only a coarse grid which seems relevant and promising to experts (Kotachi, Rabadi & Obeid 2013).

4 Results and Discussion

The literature search described in Section 3 discovers recent publications which have used simulation-based optimization at container terminals, covering lots of different problems, ranging from optimization tasks in everyday work life to supporting major investment decisions. Especially the short-term optimization tasks are described as some kind of scheduling problems, i.e. the solution is an efficient sequence of jobs. The long-term decision problems, such as layout determination and equipment purchases, are reflected by discrete or continuous values.

4.1 Permutation Space

In Table 1 the compilation of different simulation-based optimization approaches which deal with permutations is presented. In addition to the already mentioned scheduling problems, the Tug Pilot Assignment Problem (TAP), the Quay Crane Dual-Cycling Scheduling Problem (QCDS), the Storage Space Allocation Problem (SSAP), the Vehicle Dispatching Problem (VDP), and the Sequencing of Optimization Problem (SOP) are covered. The ampersand (&) indicates the integration of several problems. Mostly Ge-

netic Algorithms (GA) are used, and second most Particle Swam Optimization (PSO). Here the ampersand indicates that two algorithms were intertwined. The algorithm on the left side is on the upper level, while the algorithm on the right side of the ampersand is on the lower level. Simulated Annealing (SA), Taboo Search (TS) and Beam Search (BS) are used less frequently. Evolutionary Algorithms (EA) are a superclass of GAs and share many commonalities. The solution space matrix is derived from the graphical or textual description of the solution representation. This was not necessarily the internal representation during the search process, e.g. the implementation following the BS methodology constructs the solution based on several sets. Furthermore, neighborhood definitions often needed for SA are not accounted for. Yet, the shape of the solution space determines which algorithms can be used. The number sign (#) followed by an equipment type represents the number of distinct machines - similarly for tasks, containers or facilities on the container terminal. Here, one- or two-dimensional matrices have been used. One-dimensional matrices decode the sequence of tasks and use specific schemes for the assignment to different machines. The second dimension is mostly used for distinguishing between different types of equipment or the different instances.

The literature deals with many different equipment scheduling problems (QCAP, QCSP, QDCS, YCSP, VDP, TAP), problems related to area usage (BAP, SSAP), and the determination of a sequence of how to optimize different problems at a container terminal (SOP). It can be seen that even when two publications cover the same problem, the way the results are obtained always differ. Not two publications work on the same problem with the same algorithm, and a solution space of the same shape. This makes it difficult to draw conclusions directly.

Table 1: Simulation-based Optimization in the Permutation Space

Reference	Problem	Algorithm	Solution Space Matrix Dimensions
Al-Dhaheri, Jebali & Diabat 2016	QCSP	GA	$\#QCs \times \#bays$
Arango et al. 2013	BAP	GA	$\#vessels\ x\ 60$
Cordeau et al. 2015	SSAP	SA, TS	$\#housekeeping\ tasks$
Gudelj, Krčum & Čorić 2017	VDP	GA	$\#tasks + 2 \cdot \#projects + \#equipment$
Haoyuan & Qi 2017	QCSP	GA, PSO, SA	$\#ship\ areas\ with\ tasks$
He, Huang & Yan 2015	YCSP	GA & PSO	$\#tasks \times 2$
He et al. 2015	VDP & YCSP & QCSP	GA & PSO	$\#tasks\ \times\ 3$
Olteanu et al. 2018	QCAP & QCSP	GA	$\#Q\ \times\ \#assigned\ cont's$
Said & El-Horbaty 2015	SSAP	GA	$\#storage\ blocks$
Supeno, Rusmin & Hindersah 2015	VDP	GA	$\#transp.\ tasks + \#YTs$
Zeng, Diabat & Zhang 2015	QDCS	GA & GA	$2 \cdot \#rows + 1,$ $\#cont's\ to\ load$
Zhao et al. 2015	SSAP	GA, PSO	$\#stacking\ instructions$

A yet untouched topic is the interpretation of the solution space. When decoding a single sequence into a schedule covering several machines, in literature many approaches exist. It remains an open question whether some encoding schemes have superior properties for the solution space exploration and exploitation. All solutions are represented by a one- or two-dimensional matrix. Often some of the complexity is delegated to problem-specific algorithms for fixing infeasible solutions as well as the encoding and decoding of the problem into actions in the simulation model. For PSO, one viable way is to translate the discrete space into a continuous space for the search phase and translate it back into the discrete space before translating the sequence into measurable actions inside the simulation model (He, Huang & Yan 2015a).

4.2 n-dimensional Discrete and/or Continuous Space

In Table 2, a summary of the reviewed studies is presented. The variable K_i simply represents a decision variable which is of continuous nature. The type of two decision variables could only not be verified for the publication of Leriche et al. (2016) because of a lack of provided details. This is indicated by an apostrophe. In the Table, different problems are in focus: Four of the publications deal with the terminal layout and equipment. In addition, parameters for a rail system or an empty container policy are tuned. Like in permutation space, GAs prevail. Other employed meta-heuristics are EAs, Scatter Search (SS), and Glow-worm Swarm Optimization (GSO).

Among the publications in Table 2, Kotachi et al. (2018) tunes the largest number of distinct facilities simultaneously, covering the berth layout (length of berth), yard layout (number of import and export rows, number of YCs per row) and the gate (number of lanes). Due to this complexity, first

the sequence of the optimization tasks was solved in the permutation space (see the previous section). Four of the seven publications deal with block planning, general layout planning and equipment purchases. The decisions are of high impact and due to the differences between container terminals the answers of the studies can hardly be generalized. Yet a conceptual framework is of interest in the industry (Lin, Gao & Zhang 2014; Kotachi et al. 2018). For policy parameter tuning, the previously listed BAP is addressed again. Here, parameters of a decision support module are tuned (Ursavas 2015).

Table 2: Simulation-based Optimization in the n-dimensional Discrete and/or Continuous Space

Reference	Problem	Algorithm	Solution Space
Haoyuan and Dongshi 2016	Block Planning	GA	$\{0,1\}^{36}$
Kotachi et al. 2018	Layout & Equipment	EA	$K_1 \times K_2 \times K_3 \times K_4 \times K_5 \times K_6 \times K_7$
Leriche et al. 2016	Rail system parameters	SS	$K_1 \times K_2' \times K_3'$
Sáinz Bernat et al. 2016	Empty container policy parameters	GA	$\mathbb{N}^2$
Shahpanah et al. 2014	Layout & Equipment	GA	$\mathbb{N}^4$
Ursavas 2015	BAP Priority Control Policy Parameters	SS	$\mathbb{R}^{\#vessel\ classes}$, $\mathbb{N}^{\#berths \times \#vessel\ classes}$
Zukhruf et al. 2017	Equipment	GSO	$\mathbb{N}^2$

Similarly, Sáinz Bernat et al. (2016) tune parameters which are used for an empty container policy. At this point, optimization works on a meta-level and does not optimize the actual problem anymore.
In total, in three out of seven cases GAs are used, and all search algorithms (i.e. GA, EA, SS, and GSO) are population-based meta-heuristics. Interestingly, at no point Random Search (RS) has been used as a baseline. RS has shown better search results than human-guided search processes in other domains (Bergstra & Bengio 2012). Any meta-heuristic needs to be better than random to contribute to the optimization process.

5 Conclusions and Future Research Directions

Several publications hardly vary the parameters which control the behavior of a meta-heuristic. In addition, little justification is given for the reason why a meta-heuristic has been chosen. This might be a very challenging task. If one knew the exact behavior of the complex system, one would not need simulation. If one knew sufficiently good rules of thumb for the decision problems at hand, one would not need optimization. Therefore, arguing for a specific meta-heuristic with specific parameter values is difficult. Sörensen (2015) argues that by deconstruction one can gain deep insight into how each of the components of a meta-heuristic work. Watson, Howe & Darrell Whitley (2006) showed how a tabu search algorithm can be examined by running different experiments. Such steps help to understand why certain performance measures are obtained - something that might be more helpful than just obtaining and reporting better scores. To give one example, He et al. (2015a) and He et al. (2015b) use GA & PSO while He

(2016) use GA & SA for different types of scheduling problems. The theoretical reasoning or initial empirical evidence for why in the third scientific contribution GA & PSO is not applied could be of further interest. In this regard, the research about meta-heuristics for maritime research problems is in its infancy.

5.1 Limitations of This Literature Review

The search was restricted to a short time range of five years, thus it could not detect developments over a longer time period. The search terms were chosen with care but the fusion of optimization and simulation goes by different names, so some publications could have stayed undetected. The large scope of covering all kinds of simulation in the scope of a single container terminal resulted in some typically reported optimization problems (see e.g. Gharehgozli et al. 2016) and some rather specialized issues, especially in the n-dimensional discrete and/or continuous search space. This wide range limits how the optimization approaches can be reasonably compared. For this reason, the contentual perspective is lacking, such as the practical and theoretical assumptions made, or how a found solution representation is exactly interpreted in the simulation model. In some publications, several intermediate solution representations were presented. This could not be sufficiently covered in the overview. Furthermore, similar optimization problems exist outside container terminals (Xu et al. 2015). The focus on one container terminal limits the covered literature and neglects problems which are similar in theory.

5.2 Future Research Directions

The aforementioned limitations create great opportunities for future explorations: When focusing on one problem (or a group of similar problems), by far more criteria can be examined and compared meaningfully. On the one hand, the contentual perspective needs to be elaborated. A fair comparison of different optimization strategies needs to take into account which conceptual model and simulation model have been developed and which assumptions have been made. On the other hand, the algorithms can be examined in more detail, including the algorithm selection and parameter tuning process.

In general, the search process of meta-heuristics needs to be further investigated. Sörensen (2015) advocates to intensify the research less on the pure performance of a meta-heuristic but more on the how and why. In this literature review, GAs have been used in 16 out of 25 publications. What is the reason behind that? How promising are other meta-heuristics? An in-depth analysis of the search behavior can possibly provide the reasoning for the selection of the most appropriate algorithm in future.

Only a few instances of meta-heuristics operating in the n-dimensional discrete and/or continuous space have been presented. As Kotachi et al. (2018) argue, this is one essential approach in the field of terminal planning. The same type of solution space has been of great interest in the automated machine learning community as well (Bergstra et al. 2011; Hutter, Hoos & Leyton-Brown 2011). It remains an open research question how well the meta-heuristics can be applied to simulation models. Different meta-heuristics alongside with different meta-heuristic parameters need to be empirically compared to gain more insights.

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