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COMBINING OPTIMIZATION AND AUTOMATIC SIMULATION MODEL GENERATION FOR LESS-THAN-TRUCKLOAD TERMINALS

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ABSTRACT

Recent advances allow Less-Than-Truckload (LTL) terminals to know the distribution of arriving goods on inbound trucks in advance. Therefore, assigning docks to inbound and outbound relations and trucks to docks is a critical problem for terminal operators. This paper introduces a framework combining automatic model generation and optimization. The approach aims to allow testing of suggestions from multiple optimization algorithms. The relevance and feasibility of this approach in finding an appropriate optimization algorithm for a given system are demonstrated through a simplified case study of a variation of the dock assignment problem. This paper demonstrates how such a combination can be constructed and how the methods can effectively complement each other, using the example of LTL terminals.

1 INTRODUCTION

One challenge associated with the use of simulation in production and logistics is the time and effort required to conduct a simulation study, which hinders the extensive use of the method. This challenge can be tackled by (partially) automating the model development process (Fowler and Rose 2004). The automatic simulation model generation (ASMG) is characterized by using a model generator that produces program code for multiple simulation models (Mathewson 1984). While various efforts have been made to achieve an ASMG (Schlecht et al. 2023), to the best of the our knowledge, there are few examples of combining ASMG approaches with optimization in production and logistics.

While simulation allows testing individual scenarios, it does not suggest solutions that are optimal on their own. Hence, one can utilize mathematical optimization, which delivers deterministic solutions, such as heuristics, to generate solutions efficiently. However, using robust or stochastic optimization to incorporate stochastic influences can have long computation times and overwhelm the mathematical model (Li et al. 2024). The combination suggested in this paper intends to exploit the advantages of both methods. However, the potential impact and limitations of combining optimization and ASMG with conventionally developed simulation models remain to be investigated.

Apart from potential methodological advances, there is practical relevance to the combination of ASMG and optimization in the LTL sector. The LTL sector is dealing with rising shipment volumes, increasing service requirements, and the operational planning of LTL terminals, which is being transformed by emerging commercial tour planning tools. One key aspect of emerging tools is the daily planning of outbound truckloads based on information about the shipment distribution on inbound trucks. This planning approach differs from assigning shipments to fixed relations used previously. Based on the available data, it can be determined whether adjusting the dock assignments on a daily basis is worthwhile. Due to the daily updated data, the decision must be made within a few hours, which limits the use of simulation studies. In addition, the LTL sector is characterized by small and medium enterprises (SMEs) whose use of simulation is hindered by the costs (Yu and Zheng 2021). These factors favor the development of heuristics with short runtimes for SMEs. However, SMEs must select an appropriate algorithm and determine suitable parameter settings to obtain the best possible solution for their specific terminal and problem. A general-purpose algorithm applicable to various SMEs is hardly realistic. Furthermore, optimization algorithms would then only optimize on their specific objective function. Therefore, one possibility is to test suggestions of multiple optimization algorithms and parameter settings with stochastic influences and target variables via simulation. One option to make the described possibility available to SMEs is to combine ASMG and optimization.

Publications on optimizing the dock assignment are available for a wide range of problem settings, primarily for cross-docking terminals. Though cross-docking terminals differ from LTL terminals, they share similar functional areas and processes. Process implementation differs, e.g., in the schedules and quantities of goods and trucks. However, the unloading and loading processes, as well as the temporary storage of goods in staging areas in front of docks, are performed in both terminal types. Hence, publications on LTL and cross-docking terminals are included to provide a more comprehensive range of solutions for the dock assignment. In this respect, this work aims to show the feasibility of linking ASMG and optimization. However, it does not present an industry-ready solution for the LTL sector.

The contribution lies in an initial effort to combine automatic model generation and optimization. In Section 2, relevant literature is reviewed regarding using ASMG in the combination of simulation and optimization. In Section 3, a framework is developed that combines an existing block-based ASMG approach with optimization, representing the methodological contribution. The framework is eventually implemented in Section 4 and Section 5 using an application-oriented, but simplified case study. This results in a practical contribution that demonstrates the feasibility and relevance of combining optimization and automatic model generation in coping with real-world problems.

2 LITERATURE REVIEW

2.1 Automatic Simulation Model Generation

Various approaches characterize the field of ASMG research (Schlecht et al. 2023; Reinhardt et al. 2019). The shared basis of the approaches is using a model generator, which creates new executable simulation models (Mathewson 1984). This distinguishes the ASMG from generic modeling, which allows model variations via variables instead of creating new program code (Pidd 1992).

The classification of existing ASMG approaches can be found in Bergmann and Straßburger (2010) and Gmilkowsky et al. (1998), among others. They classify the approaches according to their generation techniques as parametric, structural, or hybrid-knowledge-based. Additionally, the planning phase, data input type, and application sector are used for classification (Wenzel et al. 2019; Vieira et al. 2018).

For the application of ASMG, Gocev and Rabe (2010) developed a data input module for graphical layout planning in the early phases of manufacturing planning. In contrast, Selke (2004) and Lugaresi and Matta (2021) adopt a different approach and apply ASMG using system data. Furthermore, Bessai (2019) generates model variants by reusing existing components in simulation models with the help of combinatorial logic. Additionally, Jurgeleit et al. (2024) present a tool for the LTL sector relying on a parametric approach combined with generic modeling designed to be used by nonsimulation experts.

Besides technical implementation, a fundamental challenge in ASMG comes with verification and validation (V&V), as existing techniques are restricted to automatic applications. The automation capability of various V&V techniques is discussed by Langenbach and Rabe (2023).

In general, ASMG can reduce the effort and can be used to cover a wide range of model variations. However, ASMG, like simulation in general, does not provide deterministic solutions.

2.2 Mathematical Optimization

Using mathematical optimization is a well-established method for obtaining a deterministic solution to a specific model and problem formulation. One example is the assignment problem that maps one set to another with a bijection, i.e., one element from one set is mapped to one and only one element of another set (Burkard et al. 2012).

One variation of the assignment problem is the dock assignment of LTL and cross-docking terminals. As reasoned in Section 1, we include literature of both terminal types to ensure a broad range of approaches to address the dock assignment problem. This is a relevant topic for practice, underlined by the review paper from van Belle et al. (2012) who defined the cross-docking assignment problem as determining where each inbound and outbound docks are located within a given set of docks. They argued that this problem is usually more complex than the classic assignment problem due to multiple influencing factors and decision criteria.

Bartholdi and Gue (2004) determined that the shape of the terminal is essential for terminal management and found that its best shape depends on the size. They included the cross-docking assignment problem in their work, suggesting an algorithm that assigns inbound docks to the center and initially sets up the most frequently used outbound relations, corresponding to the outbound docks, as close to the center as possible. A pairwise exchange algorithm for the outbound docks follows that minimizes costs.

Multiple factors can be included when determining the dock assignment of a cross-dock. For example, Motaghedi-Larijani (2022) investigated the number of cross-dock outbound doors to open, considering the vehicle routing problem for recipients of the outbound relations of the cross-docks. The author also considered the scheduling of trucks at outbound doors within a bi-objective model and connected a simulated annealing algorithm after a local search approach. Aberka et al. (2024) also considered scheduling trucks to inbound and outbound docks. They developed a Mixed-Integer Programming formulation to decide on the cross-dock assignment, which is also done by Theophilus et al. (2021) and Yu et al. (2023). The latter additionally considered the uncertainty of customer demand. They used a robust optimization approach, which can include worst-case data assumptions. However, they concluded that one of their crucial limitations is dealing with uncertainty and described that stochastic optimization could improve solution quality in the future, but would lead to problems regarding information availability and traceability. Recently, machine learning algorithms, combined with Branch-and-Cut algorithms, gained interest as a method for problems related to cross-dock and LTL-terminals, especially for truck scheduling (Neamatian Monemi et al. 2023; Neamatian Monemi et al. 2024).

As such, mathematical optimization is a standard and established method for many decisions regarding cross-docking terminals. Possible influencing factors to incorporate are truck schedules or demand uncertainties. However, when dealing with stochastic factors, limitations of the method alone become apparent, and using stochastic optimization also has its drawbacks. Therefore, combining simulation and optimization offers to incorporate stochastic influences and obtain a deterministic solution.

2.3 Combination of Simulation and Optimization

While optimization delivers deterministic solutions, simulation is frequently employed to test different scenarios with stochastic influences and assess the impact of decisions more thoroughly. Furthermore, mathematical optimization can face limitations due to the potentially extensive effort required to model various factors affecting logistics processes and the complexity of the model, which results in lengthy computation times. In contrast, simulation is an effective method for examining the relationships between different subsystems. It captures complex interdependencies and facilitates a simplified analysis of stochastic influencing factors and the temporal dynamics of systems. Therefore, combining these methods potentially facilitates decision-making for complex applications (Juan et al. 2015).

Clausen et al. (2012) used simheuristics to improve processes in LTL terminals and, more specifically, the traveling times, distances, and utilities of forklifts. However, the authors did not investigate dock assignments and focused on reassigning internal pickup areas and different forklift dispatching strategies. A tabu search determined solutions for dispatching and assignments, while a simulation evaluated the effects of the chosen solution. The authors demonstrated improved efficiency with their approach and concluded that it is well-suited for LTL terminals to incorporate realistic requirements and support strategic decisions.

Exact algorithms can also be connected to simulation models as was done from Kiefer et al. (2024). The authors combined a simulation model with an optimization module that determines solutions with an optimization solver from the MIP formulation. Generally, simulation optimization approaches are crucial in complex, real-world problems in supply chain management for decision support in Industry 4.0, and smart manufacturing (Ghasemi et al. 2024).

VDI 3633 Part 12 (2020) defines four combination methods of simulation and optimization, depicted in Figure 1. Either the optimization and simulation modules are connected sequentially, where one module strictly follows the other, or one module is integrated into the other. The first method is generally used when one of the two modules does one task and the other builds up on the obtained results, while the latter method is used when one module is one subcomponent of the other module.

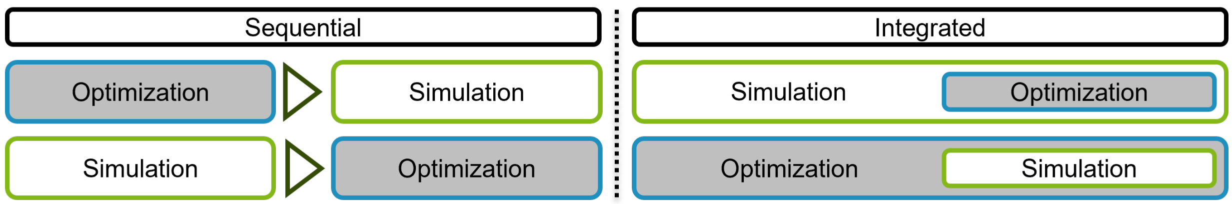

Figure 1: Categorization of combination methods of simulation and mathematical optimization based on VDI 3633 Part 12 (2020).

Efforts to combine ASMG approaches and optimization are scarcely available. One contribution in this field is provided by Ng et al. (2011). They combined ASMG and optimization and determined the factory flow design in the early planning phases. While the combination of simulation and optimization is generally an established method, the potentials and risks of combining ASMG with optimization have yet to be discussed.

The contribution that this work aims to provide lies in the effort to combine automatic model generation and optimization. In reference to the reviewed literature, this work is located next to Ng et al. (2011). To provide this contribution, an existing ASMG approach (see Section 2.1 is expanded to include existing optimization algorithms (see Section 2.2). The combination of existing examples and guidelines as described above is taken into account.

3 METHODOLOGY

In the following section, an initial effort is made towards combining ASMG and optimization by conceptually expanding an existing ASMG approach. The aim is to create a combination that allows testing suggestions of multiple algorithms and parameter settings. The underlying objective is to enable SMEs to make a well-informed decision about which optimization algorithms provide suitable suggestions for their specific terminal. A crucial requirement is to enable use with limited expertise in simulation and optimization. For this purpose, a suitable ASMG approach described in Section 2.1 is selected, which is then combined with an optimization module based on the guidelines of VDI 3633 Part 12 (2020). The resulting approach is implemented in Section 4, in which heuristics are selected based on the literature from Section 2.2.

For the use case under consideration, optimization algorithms should provide multiple suggestions that are to be evaluated through simulation experiments. For this purpose, the sequential combination with the optimization module preceding the simulation module according to VDI 3633 Part 12 (2020) is selected.

The ASMG approach chosen to be extended by combining it with optimization is the approach of Jurgeleit et al. (2024) as the approach is designed for non-simulation experts and has already been implemented for the LTL sector. Jurgeleit et al. (2024) developed an ASMG framework tailored for SMEs with the following key features that are relevant for the extension by an optimization module. The framework consists of components ranging from input to model generation and output of results, which are arranged in a layer structure. The layer assignment indicates which group of users has access to the components. Layer 1 users require ASMG knowledge, Layer 2 users require simulation knowledge, and Layer 3 users do not require simulation knowledge. The model generation process begins with data input that is used to generate the model, utilizing predefined building blocks and predefined processes and agents. Building blocks contain, for example, paths, staging areas and docks. The generated model can then be used to perform manually conducted experiments.

To expand the given framework, an incremental procedure is employed. Initially, it is checked which components of the framework need to be modified. Subsequently, components are identified that should be added to the framework. Lastly, new components are integrated into the framework's structure.

The first change to the existing framework results from the fact that users define the terminal by using building blocks. The data about the terminal, such as the number of docks or the terminal's shape, is required for both the simulation and the optimization. To provide this data for the optimization, the model generation process is split into two steps. The first step combines the predefined building blocks according to the user's input and provides the necessary layout data. The second step builds upon the first and is intended to initialize the predefined processes and agents, as well as generate an executable simulation model.

Furthermore, the experiment is relocated in the existing framework. Experiments should be carried out automatically based on the suggestions of the optimization algorithms, allowing the user to compare the algorithms. For this reason, the component for experiments has been moved to Layer 2.

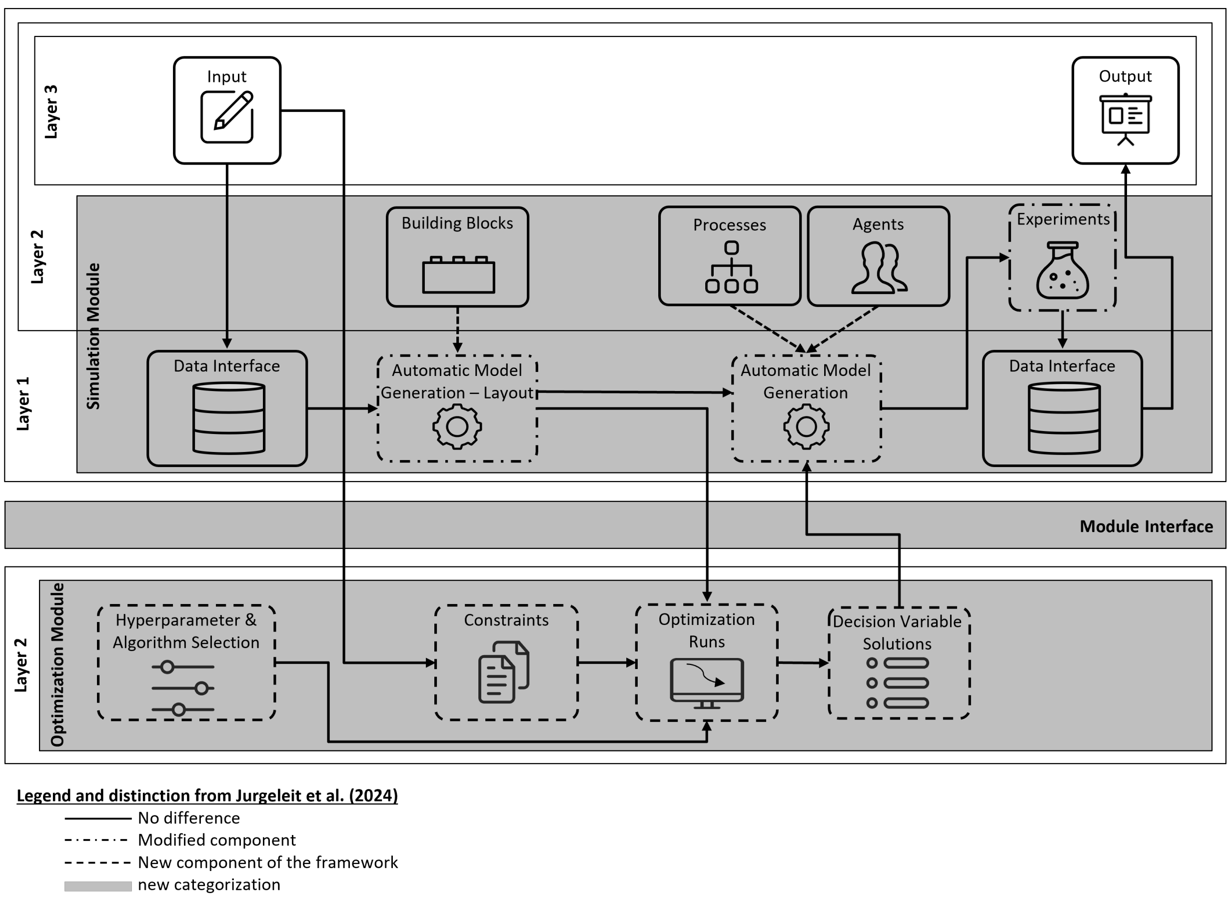

Figure 2: Description of interaction of simulation and optimization modules based on Jurgeleit et al. (2024).

New components that extend the framework are introduced by adding an optimization module. The proposed optimization module consists of four components, as depicted in Figure 2. The first component consists of hyperparameters and algorithms. This component is used to predefine a set of hyperparameters and algorithms that are to be compared. The second component consists of constraints defined by the user via the input component. An additional component executes the optimization runs. This component utilizes a predefined set of hyperparameters and algorithms, defined constraints, and terminal layout data. The results of the optimization runs are handled in the component for decision variable solutions. This component contains a set of suggestions that are to be evaluated in individual experiments. For this purpose, the suggestions must be passed to the simulation module in a suitable format. To fulfill this requirement, a module interface is added to the framework, which is responsible for any data transfer between modules including data processing and temporary data storage.

The new components described above are eventually integrated into the existing framework's structure, as shown in Figure 2. The components are assigned to the dedicated layers for this purpose. Additionally, a supplementary categorization is added to the framework to assign components to the modules. The interaction of components is visualized by directional arrows showing the direction of information flow.

The advances described above have resulted in an extended framework for combining optimization and the ASMG approach of Jurgeleit et al. (2024). The aim is to allow a simulative evaluation of suggestions from multiple optimization algorithms. The framework itself does not restrict how the components, such as constraints or the set of hyperparameters and algorithms, are defined. However, an exemplary implementation to test the feasibility of the framework follows in Section 4.

4 CASE STUDY

4.1 Problem Description and Formalization

The following case study examines terminals in which shipments arrive through inbound docks, are sorted within the facility, and depart via outbound docks. Trucks are assigned to specific inbound or outbound docks, and forklifts handle shipments. These shipments may be temporarily stored in designated pickup areas before being loaded onto outbound trucks (Ladier and Alpan 2016).

In this case study, it is assumed that the exact distribution of shipments between specific inbound and outbound trucks is known in advance, which is a realistic assumption according to Ladier and Alpan (2016). Each dock, whether inbound or outbound, is identified by a unique ID used throughout the data input and modeling process. Detailed truck schedules, including arrival and departure times, are not simplified. Future extensions could investigate these.

The objective is to determine a new assignment of docks and dock types that minimizes the total distance traveled by forklifts. This is handled in the optimization module using calculated distances. The simulation module then incorporates additional dynamic factors, resulting in actual traveled distances to test these assignments under more realistic conditions, including waiting times, congestion, and potential collisions. Any dock can be reassigned, meaning it may serve as an inbound or outbound dock.

The problem structure enables the reassignment of dock IDs to specific dock functions (inbound or outbound). Additionally, inbound trucks can be flexibly allocated to any newly assigned inbound dock, based on fixed distances between docks. The optimization outputs a dock assignment for each algorithm and passes it to the simulation module. The problem is designed to test the implementation of the framework presented in Section 3 and to determine whether different terminals require different algorithms and parameter settings.

4.2 Implementation of the Optimization Module

As discussed in the previous section, the optimization module aims to deliver "good" solutions to be passed on to the simulation module. Heuristics are considered to generate quick solutions, which is crucial for daily tour planning. There are four ways used to generate such solutions employed in this case study:

(1) ***Random***: A feasible solution is generated by assigning docks randomly.

(2) ***Central Gates*** (Bartholdi and Gue 2004): Determine the most used inbound docks to the center based on the distances to other docks. Assign outbound docks successively to the "next-central" positions.

(3) ***Local Search***: Start with the initial feasible solution from (2) and then explore *neighboring solutions* by making small changes. If a new solution improves the objective function, replace the current solution. Repeat this process for a maximum number of iterations.

(4) ***Simulated Annealing*** (Nikolaev and Jacobson 2010): Start with the initial feasible solution from (2) and then explore *neighboring solutions*. Allow for occasional acceptance of worse solutions in the early stages, enabling the exploration of a broader solution space before settling into an optimal configuration. Repeat this process until the maximum number of iterations is reached.

Generating neighboring solutions as described for the local search and simulated annealing algorithms is done by taking an initial assignment and either (a) swap two incoming trucks with each other assigned to different inbound docks, (b) shift an incoming truck to another inbound dock, (c) swap two inbound docks, (d) swap two outbound docks, or (e) swap an inbound and an outbound dock. These operations are applied with a specific *frequency*. For example, swapping inbound docks (c) may be performed 60 % of the time, while each of the other modifications (a), (b), (d), and (e) may be applied 10 % of the time each, resulting in the *frequency* be set to $[1, 1, 6, 1, 1]$. These proportions guide the generation of new solutions throughout the optimization process. Note that Bartholdi and Gue (2004) propose to use steps (d) and (e) in their algorithm. However, this case study also allows for interchanging trucks and positioning inbound docks as needed.

The simulated annealing algorithm accepts worse solutions with a probability of $P = e^{-\frac{\Delta E}{T_i}}$, where (ΔE) is the deterioration in the objective function (i.e., increase in total distance). A higher temperature T_i increases the likelihood of accepting worse solutions. T_i gradually decreases according to a cooling rate α (i.e., $T_i = \alpha T_{i-1}$) for the i-th iteration and starts at an initial temperature T_0.

Usually, parameters of algorithms such as the *frequency* of the operations mentioned above, the initial temperature, and the decreasing rate of the temperature can be tested for specific problem setups via grid-search or similar. However, as the final solution must consider multiple other influencing factors and target variables, no particular parameter testing is performed before simulation. Instead, a pre-test of the optimization module was conducted, and the frequency, initial temperature, and temperature decreasing rate were set accordingly. Different parameter combinations are then run for the algorithms, and the determined solutions are passed to the simulation module.

It should be noted that the described algorithms are only exemplary in showing the procedure of the combination approach of an ASMG and an optimization module. The algorithms in this case study can be replaced with more elaborate and problem-specific heuristics or exact approaches for improved solution quality.

4.3 Implementation of the Simulation Module and Module Interface

Based on the framework described in Section 3, the implementation of the simulation module and module interface, including a graphical user interface (GUI) for the input and output of data, is performed using AnyLogic 8.9. The GUI consists of components for defining the terminal layout, process parameters, and constraints. The terminal layout is determined by placing building blocks using a pixel-based interface. Process parameters and constraints are set numerically.

Building blocks are defined as squares with a side length of 16 meters, containing four docks, their respective staging areas, and paths for forklifts. Three predefined processes are employed, comprising unloading, loading, and handling. The handling process describes the transport of shipments from inbound to outbound docks using forklifts. Concerning the V&V, the guidelines and techniques of VDI-Guideline 3633 Part 1 (2014) are applied as far as practicable for the ASMG. Considering the objective of the case study, the V&V is considered appropriate. However, we do not contribute to the challenge of V&V for automatically generated models.

To ensure the communication between the simulation module and optimization module, the module interface is implemented using Java code in AnyLogic 8.9. As the optimization module is implemented in Python, we utilize the AnyLogic library Pipeline to facilitate data transfer between the two modules. The data transfer is done using the JSON format. Additionally, data processing functions are added to prepare the data from the optimization module.

5 EXPERIMENT & RESULTS

To address the case study described in Section 4.1, we create an experimental plan with various parameters and fixed assumptions shown in Table 1. The experimental plan contains all five terminal shapes investigated by Bartholdi and Gue (2004) and the terminal size is set to 88 docks or 22 building blocks, which is equivalent to a medium-sized terminal reflecting a large proportion of existing terminals. The number of inbound docks is set at 10 % of all docks. One forklift is assigned to each door for the unloading and loading processes, and the number of handling forklifts is set to 20 % of the number of docks. The terminal gets fully utilized according to the capacity of the outbound docks. There is no differentiation in the quantity per dock, which is equivalent to the uniform experiment setting of Bartholdi and Gue (2004). The number of inbound trucks is set to match the number of outbound trucks, which are set to be equivalent to the number of outbound docks, ensuring that each truck is fully loaded.

We define the inbound and outbound trucks for each good within the shipment distribution. Each good is placed in a uniform distribution on an inbound truck with remaining capacity, and likewise, for defining the outbound truck. In reality, however, it is more likely to have some strong relationships, depending on the terminals' location and surrounding conditions, such as those of resident companies. To consider this and investigate the impact the shipment distribution has on choosing a suitable dock assignment algorithm, we use a 15-90-20 distribution as an example, which works as follows. 15 % of inbound trucks are loaded to 90 % of their capacity with goods that have "favorite" outbound trucks. The outbound trucks of these goods are selected from only 20 % of all outbound trucks. Remaining goods are assigned uniformly across all inbound and outbound trucks with remaining capacity.

All parameter combinations resulting from Table 1 are investigated except for the collision timeout. To illustrate the impact of an extended simulation model, we only vary the collision timeout for the shipment distribution 15-90-20. Taking this into account, the experimental plan includes 315 experiments. To determine the number of simulation replications and to ensure stochastic reliability, the confidence interval is analyzed using a sample size of 20 and a variance of 1 %, considering the traveled distance of forklifts and the handling duration of pallets. The initial sample size of 20 replications is sufficient for this case study.

Table 1: Experimental plan.

Parameter	**Settings**
Layout	I, L, T, H, X
Number of Docks	88 (22 building blocks)
Distance Calculation	Rectilinear (Rec), Network (Net)
Solution Generation	Random (R), Central Gates(CG), Local Search (LS) (frequency: [[1,1,1,1,3], [2,2,1,1,1], [1,1,2,2,1]]; max_iteration: 100,000), Simulated Annealing (SA) (frequency: [[1,1,1,1,3], [2,2,1,1,1], [1,1,2,2,1]]; α: [0.8, 0.99]; T_0: 1000; max_iteration: 100,000)
Shipment Distribution	uniform, 15-90-20
Collision Timeout	[0, 2 (for 15-90-20 only)] [seconds]

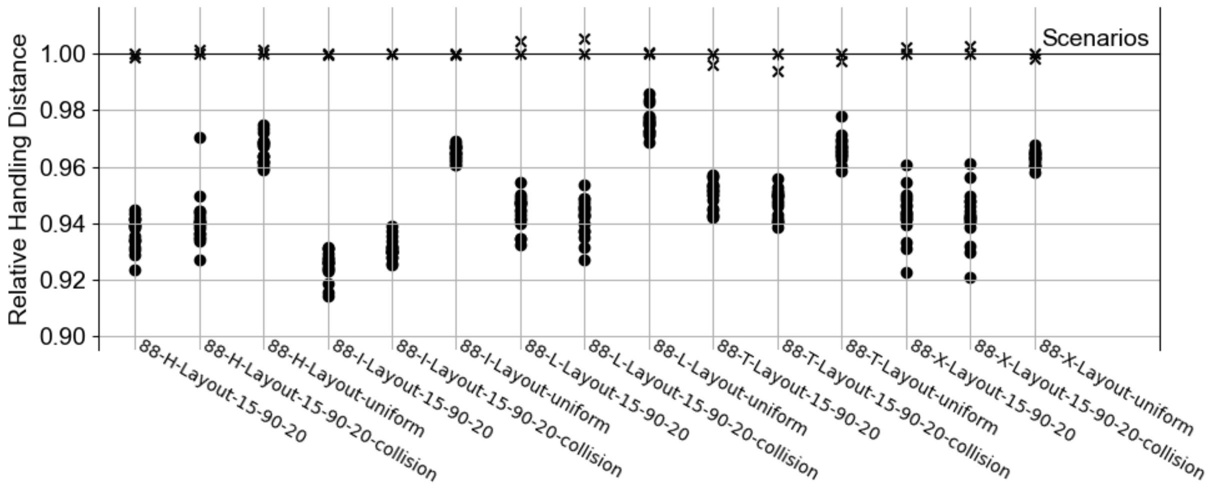

Figure 3: Relative simulated handling distances to CG-Rec solutions.

We use the term scenario to discuss the experimental results as a set of fixed and variable parameters. In the context of this work, a scenario has a fixed layout, number of docks, shipment distribution, and collision timeout but variable distance calculation and solution generation. This results in 15 scenarios, each with 21 solutions that the optimization module provides. Scenarios are referred to as, for example, *88-I-Layout-uniform*. An abbreviated solution name is, e.g., *SA-1.1-Net*. The first position defines the algorithm, and the third position defines the distance calculation. The second position comprises the parameter indices of Table 1. The frequency sets the first digit, and the second digit is set by α. Accordingly, *1.1* refers to the frequency $[1,1,1,1,3]$ and $\alpha = 0.8$.

Initially, by examining the solutions of the optimization module, we determine whether the generated solutions differ in terms of dock assignment and truck-to-dock assignment. Scenarios with an H-, L-, and T-layout have 21 unique solutions with the terms defined above, and scenarios with an I-layout have 20 unique solutions. *88-X-Layout-uniform* has 16 and *88-X-Layout-15-90-20* has 19 unique solutions regarding dock assignment, but 21 regarding the truck dock assignment.

The consideration of unique solutions can be extended to the distance calculation. We find that the way of calculating the distance affects the solutions generated. Using the same algorithm, rectilinear and network distances typically result in different dock assignments and truck dock assignments. Excluding the random solution generation, which does not differentiate between distance calculations, identical dock assignments can only be observed in three instances. When considering the truck dock assignment additionally, the number drops to two instances, which are the scenarios *88-I-Layout-uniform* and *88-I-Layout-15-90-20*. *88-X-Layout-uniform* is the third scenario with identical dock assignment solutions.

The impact of the different solutions on the simulated handling distances of forklifts is shown in Figure 3. For each scenario, distances are mapped relative to the distance from the CG-Rec solution. CG distances are crosses, and LS and SA distances are dots. Random solutions lead to longer distances and are omitted. The distances from randomly generated solutions vary between 1.15 and 1.25 times the CG-Rec distances. Figure 3 shows three main findings. Firstly, solutions generated by LS and SA result in a decrease in the handling distance. Secondly, the solution quality spread in terms of the handling distance. For example, for H-layout-15-90-20, LS and SA distances vary approximately between 0.95 and 0.92. The third finding is that the potential improvement and spread of solution quality depend on the shipment distribution and terminal layout.

Table 2 lists the best solutions depending on the layout and shipment distribution, allowing for investigating dominant algorithms and parameter setting patterns. For the top half of the figure, the best solution is determined by the smallest handling distance. No dominant solution is present for different layouts with the same shipment distribution. We observe some tendencies toward algorithm types for solutions with the same layout but varying shipment distributions. However, X- and T-layouts tend towards solutions using SA with changing parameter settings. Including a collision timeout in the simulation does not affect the best solution regarding the handling distance. An exception is the I-layout, which could be due to the small spread of I-layout solutions. Further insights can be gained if additional key figures are provided by the simulation, e.g., handling duration. The best solutions according to the handling duration are shown in the bottom part of Table 2.

Our results demonstrate that the shipment distribution and terminal shape affects the selection of an appropriate algorithm and parameter setting. Additionally, it indicates that the transferability of a statement on the best algorithm and parameter setting to other system configurations is not sound. This aligns with the statement made in the introduction that there is no general-purpose algorithm, and SMEs must find an algorithm and parameter setting suitable for their specific terminal. We demonstrate that utilizing an ASMG is promising for helping SMEs find an answer to this question.

To summarize, this case study does not provide any information about the quality of algorithms for a specific terminal due to the simplified problem description and simulation models. For this purpose, more detailed building blocks and processes must be defined, which is left for further research. The contribution lies in demonstrating that, with varying terminals and their specific characteristics, different algorithms are suitable. Furthermore, the contribution lies in demonstrating that an implementation of combining ASMG and optimization according to the framework described in Section 3 is feasible and can help find an appropriate algorithm and parameter setting.

Table 2: Algorithm setups that minimize considered key variables for an experiment scenario.

Simulation Handling Distance					
	I	L	T	H	X
Uniform	SA-2.1-Net	LS-2-Rec	SA-3.1-Net	LS-2-Net	SA-2.2-Net
15-90-20	LS-2-Net	SA-1.1-Rec	SA-2.1-Rec	LS-1-Rec	SA-1.2-Net
15-90-20-collision	LS-3-Net	SA-1.1-Rec	SA-2.1-Rec	LS-1-Net	SA-1.2-Net
Simulation Handling Duration					
	I	L	T	H	X
Uniform	LS-2-Rec	SA-2.2-Rec	SA-3.1-Net	SA-2.2-Rec	SA-1.2-Rec
15-90-20	LS-2-Rec	SA-2.1-Rec	SA-3.2-Net	LS-2-Net	SA-1.2-Net
15-90-20-collision	SA-1.1-Net	SA-2.1-Rec	SA-3.2-Net	SA-1.2-Net	SA-1.2-Net

6 CONCLUSION

This paper presents an approach that combines mathematical optimization and simulation to assess solution suggestions given by a collection of heuristics against multiple layout variations using ASMG. A variation of the dock assignment problem is introduced, utilizing the proposed framework. In line with the emerging operational planning of LTL terminals, the variation supposes a fixed shipment distribution on outbound and inbound trucks.

The investigation encompasses five terminal shapes and four heuristics, each with a range of parameters, resulting in a total of 315 experiments. The experiments suggest that shipment distribution affects the choice of a suitable heuristic. In addition, the terminal shape influences the choice of heuristics. No heuristics or parameters that dominate across different shipment distributions and terminal shapes could be found. This demonstrated that a statement about the value of a heuristic can only be made for specific systems, not for a general problem. Therefore, different algorithms and parameter combinations need to be tested for each instance to find an appropriate solution. Simulation can support this task. Therefore, the sequential combination of ASMG with optimization was exemplarily demonstrated. Studies that include different layout variants can benefit from this approach and potentially be accelerated by ASMG. Different combinations of parameters within heuristics can determine optimal solutions for different input data, which makes testing multiple parameters for each problem setup sensible.

However, this paper does not contribute to the effective validation of automatically generated models. Additional extensions, such as more advanced optimization algorithms, iterative linking, and other combination methods regarding ASMG, are left for future research. Moreover, further research could focus on enhancing the level of detail and leveraging the benefits of simulation to a greater extent.

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