*Proceedings of the 2017 Winter Simulation Conference*
*W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page, eds.*

# A COMBINED SIMULATION OPTIMIZATION FRAMEWORK TO IMPROVE OPERATIONS IN PARCEL LOGISTICS

Moritz Poeting
Jonas Rau
Uwe Clausen

Institute of Transport Logistics
TU Dortmund University
Leonhard-Euler-Str. 2
Dortmund, 44227, GERMANY

Christin Schumacher

Chair of Modeling and Simulation
TU Dortmund University
Otto-Hahn-Str. 16
Dortmund, 44227, GERMANY

## ABSTRACT

Operators of parcel transshipment terminals face the challenge of sorting and transferring a large number of parcels efficiently. In order to meet customer expectations, short sorting intervals are required. In this paper we present a technical framework that combines metaheuristics with discrete-event simulation (DES) to provide robust solutions for problems at the operational level of parcel transshipment terminals. First, the framework applies metaheuristics such as local search solve the problem of scheduling incoming trucks as well as allocations at the loading gates taking into account the characteristics of the internal sorting system. Next, detailed conclusions on the real system behavior are drawn by testing the solutions in multiple DES experiments with stochastic processing times. The paper presents first results using our framework and investigates the procedure with regard to the solutions quality and runtime requirements.

## 1 INTRODUCTION

The parcel delivery industry has become a significant market within the transport industry. Market participants have specialized in the universal delivery of mainly standardized low weight shipments. Several factors such as the increasing demand for time-critical delivery, the trend towards smaller Unit Loads, and the rapid rise of e-commerce facilitate this development and result in a continuous growth of parcel logistics. In order to preserve existing delivery times, established parcel service providers face the challenge to adjust their logistical networks as cost-effective as possible. With regard to requested short delivery times (e.g. in e-commerce) especially handling speed is an important factor. Therefore, automatic sorting has become the industry quasi-standard and finding efficient configurations for terminals has become an important factor of success (Schwemmer 2016).

The material flow of a parcel transshipment terminal consists of three main process steps. First, incoming vehicles are assigned to unloading docks and manually unloaded. Second, the parcels are sorted by an internal network of conveyors according to their dedicated destination. Finally, the parcels are manually loaded into outgoing vehicles (Clausen, Diekmann, and Dormuth 2015).

In the field of simulation and optimization, there are different approaches evaluation and optimizing the sorting process at transshipment terminals. Their main objective is to maximize the degree of capacity utilization in the internal sorting system. Existing models differ in methods of optimization, level of detail, and process of linking optimization and simulation.

In this context, Clausen et al. (2017) present an approach to couple DES with a mathematical optimization model. The combined modeling approach merges both methods in a combined procedure. Results for the simulation and the optimization models are computed on separate systems. While simulation experiments

978-1-5386-3428-8/17/$31.00 ©2017 IEEE

are computed within a few minutes, finding near optimal solutions with an exact optimization model takes several hours. To overcome this problem, Schumacher (2016) developed suitable heuristics for the problem and Schumacher et al. (2017) present primary results combining DES with an advanced local search algorithm.

Our objective is to expand this concept by connecting fast metaheuristics and DES into an integrated framework. This framework is capable of performing large sets of simulation experiments to evaluate the effect of stochastic system behavior on solutions.

Therefore, research findings concerning heuristic optimization of logistic terminals and simulation optimization frameworks are introduced in the second section. An overview of different approaches to combine simulation and optimization are presented with respect to their main advantages and disadvantages. The third section deals with the definition of the mathematical model, the implemented metaheuristics, and a description of the adapted simulation model. The architecture of the automated framework and the applied procedure are described in the fourth section. In section five, we present the experimentation process and first results related to the robustness of the obtained solutions. Finally, the findings of the presented approach are summarized and a future research perspective is outlined in the last section.

## 2 RELATED WORKS

Various authors give overviews about different techniques to connect simulation and optimization such as Figueira and Almada-Lobo (2014) or simulation and metaheuristics such as Gutjahr and Pichler (2016).

The Simheuristic approach introduced by Juan and Rabe (2013) is a powerful technique defined as a combination of heuristics or metaheuristics with simulation techniques in order to efficiently solve stochastic optimization problems. In further studies Grasas, Juan, and Lourenço (2016) present different SimILS frameworks that extend ILS (iterated local search) with the possibility of combining it with simulation techniques. Their approach allows coping with stochastic combinatorial optimization problems. Bayliss et al. (2016) present a practical application by transferring Simheuristics to the vehicle ferry revenue management problem. In a first step they use a loading simulator in order to reduce the state-space of the dynamic program, which enables it to use dynamic pricing to solve the pricing problem in a second step.

A widely used method to combine simulation and mathematical optimization is simulation-based optimization (SBO). These concepts are applied to diverse areas such as economics (Bayliss et al. 2016), the chemical industry (Jung et al. 2004), or logistics (Avci and Selim 2017).

There are two groups in the research field of combining mathematical optimization and DES for parcel transshipment terminals. The research group around McWilliams applies heuristics while the research groups of Clausen and Ladier solve exact optimization models and establish a combination of both methods.

McWilliams' first experiments use SBO algorithms, which compute the value of the objective function by simulation take computation times of several hours (McWilliams, Stanfield, and Geiger 2005; McWilliams, Stanfield, and Geiger 2008; McWilliams 2005; McWilliams 2009). Their findings therefore coincide with the findings of Jung et al. (2004) who also consider the long computational times as a disadvantage of SBO. Hence, in their further research publications they use a more usable method, which deterministically generates objective function values. Simulation results are merely used to verify the mathematical model. With this method, McWilliams (2009) introduces a genetic algorithm with the simplification of equal unloading times and McWilliams and McBride (2012) apply a beam search heuristic. However, for larger sized problems the computational times of beam search heuristics are significantly worse compared to the genetic algorithm of McWilliams (2009). McWilliams (2010) compares local search and simulated annealing with the genetic algorithm of McWilliams (2009) in the circumstance of unequal unloading durations, observing local search and simulated annealing outperform the genetic algorithm.

The approach of Ladier, Alpan, and Greenwood (2014) differs from McWilliams' method by utilizing mathematical optimization and simulation as two equally relevant methods. In detail, they evaluate the robustness of integer program solutions using DES in context of truck and pallet schedules for a cross-docking facility. The simulation uses stochastic events such as transfer time, unloading time per pallet and truck arrival times, which are not taken into account in the integer program (IP). In order to see how robust the calculated schedules are, the deviation between the performance of the generated schedule and the initial deterministic performance are compared within 20 replications for multiple simulation scenarios of 21 instances. In the resulting publication of Ladier and Alpan (2016), various reformulations of the cross-dock truck scheduling problem are introduced in order to improve the robustness of the calculated schedules compared to Ladier, Alpan, and Greenwood (2014). They conclude that minimizing the average number of trucks docked at a given door is a good way to ensure robustness in the schedules.

Furthermore, Clausen's approaches especially differ to the studies of McWilliams' research group, in the way the number of time slices can be variably chosen. For the whole process of the transshipment terminal, each time slice has a constant length and thus the unloading of trailers can start as soon as a gate is available. Apart from this, Clausen's approach focuses on the equal combination of mathematical optimization and DES. Here, after solving an exact mathematical optimization model the results are transmitted into a DES model with stochastic factors. The purpose is to enhance realistic modeling for simulation and optimization. To achieve an improvement, for instance, the constraints of the optimization model are adapted using simulation results. In addition, Clausen et al. use decision variables to determine which outbound relations are assigned to a sorter. In their research, Diekmann, Baudach, and Clausen (2014) use a small system of parcel transshipment terminals. Clausen et al. (2015) found that the mathematical and simulation approach can easily be adapted to larger systems without reducing the solution's quality. Thus, the examined small system is also the research focus of this paper. Clausen et al. (2015) conclude that the best objective function is to minimize the makespan followed by using an objective function to achieve a uniformly distributed utilization of the sorters. Additionally, different data sets are generated by Clausen, Diekmann, and Dormuth (2015) using statistical methods. Finally, Clausen et al. (2017) reduce the time slice's length to one minute, without significantly increasing complexity and runtime. Furthermore, all of Clausen's studies are based on different unloading durations and arrival times of the inbound trailers during the sorting process. This aspect adds an important realistic detail. The disadvantages of Clausen's approaches are computation times of several hours required by the exact solving procedures, compared with McWilliams' metaheuristics.

Schumacher (2016) eliminates above described limitations for practicality and additionally includes changeover times. Schumacher (2016) concentrates on mathematical methods to solve the problem with an evaluation of several scheduling algorithms and metaheuristics. These algorithms require computation times of maximum four minutes. Schumacher (2016) also evaluates that the solution's quality is comparable to the results of Clausen's exact model. Schumacher et al. (2017) provide initial steps for combining this approach with the simulation. However, automated linking and the resulting possibility to determine robust solutions is still incomplete and is the focus of this paper.

## 3 SIMULATION AND OPTIMIZATION OF PARCEL LOGISTICS

In the subsequent section the mathematical model and the local search algorithm are introduced. In collaboration, these two elements form the optimization module. The results of the optimization module are transferred via a database to the simulation model, which is described in the final paragraph of this section.

### 3.1 Mathematical Model

To create different near optimal solutions, we use the best performing algorithms for parcel transshipment terminals identified by Schumacher (2016). Therefore, some mathematical notations are introduced. Based on this, we present a local search, as the best performing algorithm.

The model's parameters were chosen in accordance with Diekmann, Baudach, and Clausen (2014). The parameter $t \in T$ describes the time slices, where each has a length of one minute. We define the arrival time of an inbound trailer $i$ as $t_i^{arrival} \in T$. $dur_i$ describes the unloading duration of trailer $i$ and *change* represents the changeover time at an unloading dock between the unloading of two trailers (Clausen et al. 2017).

The set of inbound trucks are denoted by $I = \left\{i_1, \ldots, i_{|I|}\right\}$. The trucks are unloaded at one of the unloading docks $u_1, \ldots, u_8 \in U$. The sorting system distributes the parcels to one of the main sorters $s_1 \in S$ or $s_2 \in S$.

At the loading docks, parcels are loaded onto outgoing trucks. The set of loading docks $l \in L$ is divided in 84 short distance docks $L_{short} := \{l_1, \ldots, l_{84}\}$ and 12 long distance docks $L_{long} := \{l_{85}, \ldots, l_{96}\}$. At each main sorter there are 6 long distance docks ($\left|L^s_{long}\right| = 6$) and 42 short distance docks ($\left|L^s_{short}\right| = 42$). In the transshipment terminal used in this paper, each outbound relation is loaded at one dock. Long distance outbound relations are loaded at long distance loading docks and short distance outbound relations are loaded at short distance loading docks. Analogously to the set of outbound relations $j \in J$ is divided into 84 short distance outbound relations $J_{short} := \{j_1, \ldots, j_{84}\}$ and 12 long distance outbound relations $J_{long} := \{j_{85}, \ldots, j_{96}\}$.

Concerning the objective functions in transshipment terminals, Clausen et al. (2015) determine to minimize the makespan $C_{max}$ first to be most effective. This is defined as the time between unloading the first parcel out of the first trailer and loading the last parcel on the last outbound trailer.

$$\min \quad C_{max} \tag{1}$$

Corresponding to the initialization of Diekmann, Baudach, and Clausen (2014) the allocated time slice $t$ of each inbound trailer to be unloaded is saved in the binary decision variable $x_i^t$ defined by (2).

$$x_i^t := \begin{cases} 1, & \text{inbound trailer } i \text{ is assigned to time slice } t \\ 0, & \text{else.} \end{cases} \tag{2}$$

With regard to the research of Dullinger (2008) concerning the correlation of an undisturbed sorting process and a balanced workload within the sorting system, the second aim of the mathematical model is a balanced shipment flow over all main sorters and time slices in order to avoid congestion and consequential perturbations in the sorting system. Therefore $workload_{max}$ computes the maximum throughput of a sorter over all time slices, which is minimized by (3).

$$\min \quad workload_{max} \tag{3}$$

The decision variable for this second objective is $z_j^s$, which saves the assignment of the outbound relations to the main sorters by using the decision variable (4).

$$z_j^s := \begin{cases} 1, & \text{outbound relation } j \text{ is assigned to sorter } s \\ 0, & \text{else} \end{cases} \tag{4}$$

### 3.2 Local Search

In practice, it is essential to have algorithms with short computation times. Ad-hoc modifications, such as a change in the arrival times of the trailers, can be included by solving the model again with new input data. For these fast moving operational effects, metaheuristics with their short computation times and high quality solutions are suited best.

With 1,000 as an exemplary number of iterations, Schumacher (2016) explores that (e.g. compared to simulated annealing) local search is the best heuristic for both objective functions introduced in section 3.1. For this reason, only the local search algorithms are presented and tested in the following sections using DES.

Before local search can be used to minimize the first objective function (1), a feasible schedule has to be created. Schumacher (2016) compares various procedures and comes to the conclusion that a LPT heuristic combined with a method to reduce idle time provides the best start solutions. The procedure to reduce idle time is described in detail by Schumacher (2016). Local search in Algorithm 1 improves these solutions with the 2-opt-method. This method transposes the trailers' positions in the schedule with respect to their arrival time. Algorithm 1 optimizes the objective function (1) as follows.

**Algorithm 1: Local search for scheduling**

1. Given a feasible start solution $x$ with makespan $C_{max}$ which results from an extended LPT algorithm explored by Schumacher (2016).
   Choose parameter $iterations > 0$.
2. **while** $iterations \neq 0$
   (a) Duplicate $x^n := x$
   (b) Choose randomly an unloading dock $u_a$ and an unloading dock $u_b$ in $U$
   (c) In $x$, choose randomly an inbound trailer $i_a$ that is scheduled to unloading dock $u_a$ and an inbound trailer $i_b \neq i_a$ that is scheduled to unloading dock $u_b$
   (d) Transpose $i_a$ and $i_b$ with the 2-opt-method, save transposition in $x^n$ and compute makespan $C^n_{max}$
   (e) **if** $C^n_{max} < C_{max}$
   $x := x^n$, $C_{max} := C^n_{max}$
   (f) $iterations := iterations - 1$
3. **return** $x$ with $C_{max}$

After every iteration (2a) – (2f) of local search in Algorithm 1, the algorithm to reduce idle time in the schedule is used again. Furthermore, Schumacher (2016) concludes, that for the balanced capacity utilization of the sorters the local search algorithm, which is described below, is the best heuristic. The resulting schedule of Algorithm 1 in combination with a random feasible start solution for the decision variable $z^s_j$ is the starting point for the optimization of the second objective function (3) in Algorithm 2.

**Algorithm 2: Local search for the assignment of sorting destinations**

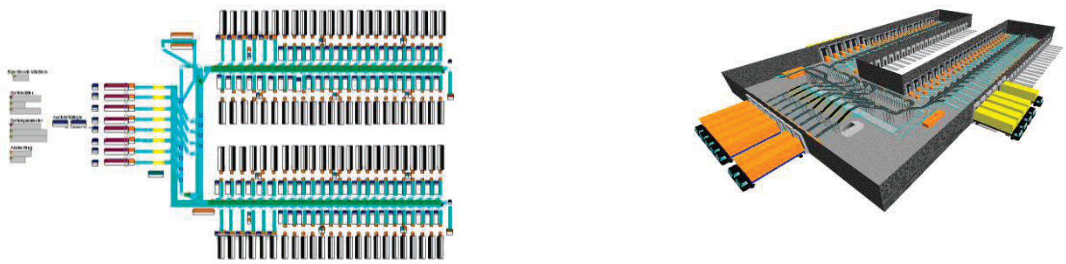
1. Given a feasible solution $x$ with makespan $C_{max}$ (which results from Algorithm 1 and stays unchanged) and given a randomly generated and feasible start solution $z$ with $workload_{max}$.
   Choose parameter $iterations > 0$.
2. **while** $iterations \neq 0$
   (a) Duplicate $z^n := z$
   (b) **while** $(j_a \in J_{short}$ **and** $j_b \in J_{long})$ **or** $(j_a \in J_{long}$ **and** $j_b \in J_{short})$
   In $z^n$, choose an outbound relation $j_a$ in $J$ which is assigned to sorter $s_1$ and an outbound relation $j_b$ which is assigned to sorter $s_2$
   (c) Assign $j_a$ to sorter $s_2$ and $j_b$ to sorter $s_1$, save changes in $z^n$ and compute $workload^n_{max}$
   (d) **if** $workload^n_{max} < workload_{max}$
   Change the all-time best solution by $z := z^n$ and $workload_{max} := workload^n_{max}$
   (e) $iterations := iterations - 1$
3. **return** $z$ with $workload_{max}$

The Algorithms 1 and 2 result in a schedule and an assignment of outbound relations to the sorters. Results are transferred to the simulation in order to evaluate them in a more realistic environment.

### 3.3 Simulation Model

The simulation model we use within the framework is created with ED Transport which was developed by the Institute of Transport Logistics (Deymann and Neumann 2008) and is based on the DES software

Enterprise Dynamics (ED). In order to create a parcel transshipment terminal, several application specific objects have been developed. The model is first introduced by Clausen and Diekmann (2012). The terminal in the model is based on the evaluation of several logistics terminals in Germany and is using real shipment data. During the observed shift, 140 trucks are unloaded with 53,419 parcels that are sorted and subsequently loaded on outgoing trucks, handling up to 4,000 parcels per hour. Parameters and process times of the terminal are implemented in accordance with the optimization model. Beyond that, the simulation enables a more detailed modeling of the manual handling processes and the internal sorting systems. A screenshot of the simulation model is shown in Figure 1.



(a) (b)

Figure 1: Simulation model layout (a) and 3D visualization (b).

For the main handling activities stochastic process times are applied to implement the variations within the process. A network of conveyors is used for the internal transport. With the simulation model, it is possible to measure the impact of congestion and to measure interdependency between different resources. In addition, different key performance indicators (KPIs) are logged during the simulation runs using the discrete time slices of one minute. This includes the makespan ($C_{max}$), the average difference over all sorters and time slices in percent ($\Delta workload$), as well as the maximum throughput per minute of the sorter ($workload_{max}$). After implementing the new interface with the framework, various testruns are conducted as verification and validation of the model. For instance, an experiment with 200 simulation runs was conducted using the same configuration as Clausen et al. (2015) to verify the correct functioning of the model.

## 4 COMBINED FRAMEWORK

We have developed an automated framework that combines the DES and the metaheuristics to find a robust configuration for the parcel terminal. In this section, the framework architecture is outlined and the technical implementation, such as the general working principles and the modules of the framework, are described.

### 4.1 Architecture

The architecture of the developed framework is shown in Figure 2. The main idea is to use decentralized components and utilize TCP/IP communication. Each object in the rectangles resemble an autonomous component of the framework. Furthermore, the SimOpt-Server contains two modules which are the communication module and the optimization module of the framework. The communication module handles requests that are submitted by the users using a TCP-Socket connection and forwards them to the optimization module that conducts the metaheuristics algorithm. To understand the interaction of the components, the procedure of an experiment can be stated as follows:

Firstly, the transportation data of the terminal is imported into the optimization module. This includes vehicle data, such as the number of trucks and the arrival interval for each truck, as well as parcel data (e.g. dimensions, weight and non conveyable (NC) information). The optimization module uses the input

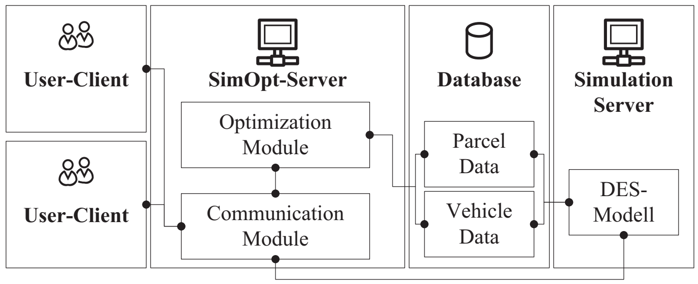



Figure 2: The architecture of the framework.

data basis to generate a feasible solution for the loading gate assignment as well as the vehicle schedule minimizing $C_{max}$ and $\Delta workload$ (see Section 3.2). The solution is stored within the database. Secondly, a whole set of simulation runs is performed in order to assess the robustness of the solution. The simulation model parameterization is automated. Therefore, the simulation model is automatically updated with the latest available data. In the first version of the framework, experiments were conducted by storing data locally using standard building blocks of ED, as per Diekmann, Baudach, and Clausen (2014). This was replaced by a custom building block using data that is stored in a MySQL database in a second phase.

The resulting loading gate assignment and the truck schedule are stored in the MySQL database to use for the current experiment. After completing the optimization run the controller module sends a message to the simulation server to start a set of simulation runs. Here, an interface has been implemented that reads the current data set for vehicles, parcels, schedule, and configuration from the database and temporarily stores them within the simulation model. Then, the adjusted number of simulation runs is performed. After each simulation run the results and KPIs are calculated within the simulation model and stored in the database. The results of the experiment include the aggregated KPIs $C_{max}$, $workload_{max}$, and $\Delta workload$ of each of the simulation runs. This allows the analysis of the KPIs using statistical methods and to draw conclusions about the robustness of the generated solution.

Figure 3 shows a schematic representation of the process. This procedure can be repeated as often as desired to create a set of possible solutions for decision makers to choose from, based on their performance and robustness.

### 4.2 Framework Components

The experiment controller's user interface is implemented in Java and consists of two components: a communication server and a user terminal client. The components communicate via network sockets using the TCP/IP protocol.

The communication server is implemented as a Java application. Users can connect to the server using the user terminal client. The communication server manages the information flow between the user in the front-end and the experiment controller in the back-end. This includes input- and output data sets as well as experiment parameters that are stored in a MySQL database and managed using JQuery.

The user terminal consists of a text box that displays server messages and a text entry box to send commands. First, the user logs in to the server by inserting the server's IP address. Then, a simulation server is selected by inserting the IP-address of a simulation client to perform an experiment. Next, an experiment is started after setting the duration of the simulation run and the number of replications. This information is stored in the experimentation table of the database. After starting the simulation runs, a command is sent to the simulation client in order to start independent simulation runs. During the simulation runtime, the current status of the runs is updated by the server and displayed to the user in the text box of the terminal.

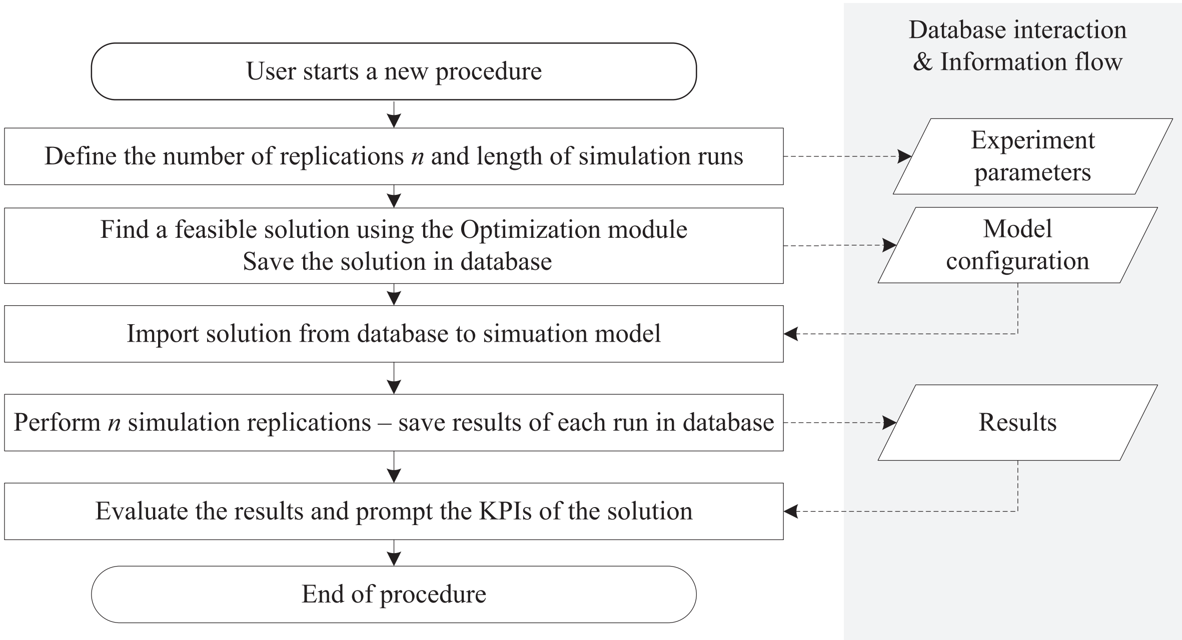



Figure 3: The experimentation procedure using the framework.

### 4.3 Simulation Model Components

For the application of the framework a new interface has been developed represented by the *SimOptController* building block in ED. The building block sets up a TCP-Socket connection to receive commands from the Java server. When receiving an incoming message that commands the start of a new experiment, the building block initializes the simulation model by updating the input data sets from the MySQL server as well as the model parameters based on the optimization results and resetting the simulation model. Then, a command loop is executed that automatically performs the defined number of experiments. The KPIs are calculated within the simulation model and after each run inserted into the MySQL database. In addition,after each simulation run a notification is sent to the Java server to keep the user up-to-date on the current state of the procedure. After the last simulation run of the current experiment, the simulation model is reset and the simulation server is ready for further experiments.

## 5 RESULTS

In this section, first results are presented that were computed using the introduced framework. Furthermore, the established KPIs are analyzed and displayed in a box plot diagram (Figure 4) to evaluate the deviation of the results.

In order to examine the impact of the stochastic values in the simulation model, three different solutions are generated using local search. In addition, one solution is developed applying the commonly used FIFO heuristic to conduct a comparative assessment to the as-is situation. The solutions generated by local search are valued with the expected makespan of 620 minutes, 622 minutes and 623 minutes, below mentioned as LS620, LS622 and LS623. Each of these results is simulated 50 times in order to ascertain their robustness under stochastic conditions. This is done by means of the presented KPIs and analyzing the belonging box plots (Figure 4). The box plots summarize different robust measures of dispersion and location. In order to unmask unequal deviation within the results, the median is compared to the arithmetic mean, which is sensitive to outliers and extreme values.

The chart on the left-hand side of Figure 4 contains four box plots showing the spread of the makespan $C_{max}$. It is particularly noticeable, that the assessed KPIs for each simulation experiment show a considerably

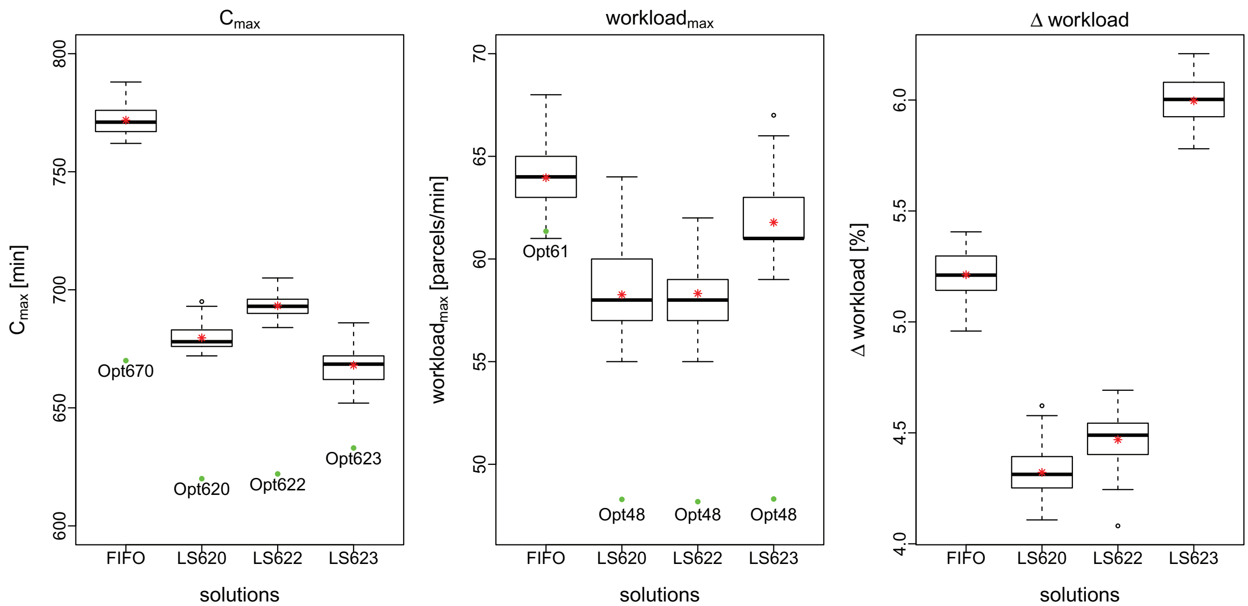



Figure 4: Box plots to compare the solutions with regard to $C_{max}$, $workload_{max}$, and $\Delta workload$

longer makespan than the optimization objective function values. This effect results from stochastic parameters in the simulation, i.e. congestion or buffer overflow. The LS620 shows a more limited spread than FIFO, as the results show a much lower value range. The median is lower than the mean value and located near the 0.25-quantile. The upper half of the data has higher variation and contains one outlier. LS622 is more symmetrical and has got a shorter box than LS620. Furthermore, the minimum makespan of LS622 is bigger than 75% of the results using LS620. Thus, both simulation and optimization results indicate that LS620 is superior to LS622. Finally, LS623 has the biggest spread in comparison to the other optimization solutions, but at least 75% of the values are lower than the minimum of LS620. Taking this into account, LS623 seems to be the best solution. Assessing only the optimization results, LS623 would have been anticipated to have the biggest $C_{max}$ in this particular comparison.

The chart in the middle contains four box plots illustrating the spreads of the $workload_{max}$. Beginning on the left, FIFO has the highest $workload_{max}$, a mean almost equal to the median, and a long upper whisker. The median of FIFO corresponds with the maximum of LS620. It is slightly smaller than its mean and also has a lower distance to the 0.25-quantile. Compared to LS620, LS622 has the same minimum and median but less spread in the upper half compared to LS620. This shows that the schedule results in a system behavior that is comparatively stable compared with the other solutions. The equality of LS623's median to its 0.25-quantile as well as the upwards outlier indicate a high variation especially in the upper 75% segment. In total, the differences between the solutions regarding $workload_{max}$ are less pronounced compared to $C_{max}$.

The chart on the right side contains four box plots which show the spread of the $\Delta workload$. Expected results of the optimization indicate a $\Delta workload$ between 0.49% (LS622) and 0.59% (LS620) while FIFO performs inferior with a $\Delta workload$ of 12.17%. In the simulation, the results of the FIFO heuristic show a symmetric box with a longer lower whisker. The equivalence of the mean and median around 4.3% suggests that solution LS620 has a symmetrical deviation of the $\Delta workload$. Solution LS622 has a higher median value than it's mean, indicating that values tend to deviate to a lower delta. Compared to the other solutions, LS623 has the highest values which are symmetrically distributed and, with around 5.9%, are still at an acceptable level.

To conclude, it can be noted that the makespan can be considered as the KPI with the most significance for the performance of the system. Therefore, solution LS623 is found to be the most promising solution for system configuration. The solution has proven to be robust after performing a large number of simulation experiments. This also correlates with the highest expected maximal throughput of the four solutions, as the analysis of the $workload_{max}$ values indicate. In contrast, merely the resulting $\Delta workload$ of LS623 appears to be higher than compared to the other solutions. However, a delta of less than 6% is still within an acceptable range.

## 6 CONCLUSION AND OUTLOOK

In this paper, we presented a Simheuristics framework that combines discrete event simulation with FIFO and local search heuristics for the optimization of transshipment terminal operation in parcel logistics. Based on the existing simulation model of Clausen and Diekmann (2012) we utilized our framework to generate and assess four solutions (one using FIFO, three using local search). All of the three solutions found by the implemented local search algorithm are superior than the comparatively presented FIFO heuristic. Additionally, it was shown that the heuristic approach offers high-quality solutions for practical application. The framework generates solutions significantly faster compared to integer programming. Furthermore, we included an extended number of replications into our procedure to deal with stochastic variation and provide an assertion about the robustness of each solution. Additional tests are planned to investigate and optimize the runtime behavior. First results underline the advantages of combining simulation and optimization in an automated framework, as it allows the evaluation of several possible solutions in multiple independent simulation experiments. Future work will additionally focus on the investigation of KPIs to have a better measurement of their robustness. Finally, we want to include more stochastic effects, i.e. fluctuating arrival times of incoming vehicles.

## ACKNOWLEDGMENTS

This paper is a research result in context of the Research Training Group ”Adaption Intelligence of Factories in a Dynamic and Complex Environment” (GRK 2193) funded by the Deutsche Forschungsgemeinschaft (DFG).

## REFERENCES

Avci, M. G., and H. Selim. 2017. “A Multi-objective, simulation-based optimization framework for supply chains with premium freights”. *Expert Systems with Applications* 67:95–106.

Bayliss, C., J. M. Bennell, C. S. M. Currie, A. Martinez-Sykora, and M.-C. So. 2016. “A Simheuristic approach to the vehicle ferry revenue management problem”. In *Proceedings of the 2016 Winter Simulation Conference*, edited by T. M. Roeder, P. I. Frazier, R. Szechtman, and E. Zhou, 2335–2346. Piscataway, NJ: IEEE.

Clausen, U., and D. Diekmann. 2012. “Simulation of transshipment terminals in the parcel delivery industry”. In *Proceedings of the European Simulation and Modelling Conference 2012*, edited by M. Klumpp, 394–398. Ostend: EUROSIS-ETI.

Clausen, U., D. Diekmann, J. Baudach, J. Kaffka, and M. Pöting. 2015. “Improving parcel transshipments operations: Impact of different objective functions in a combined simulation and optimization approach”. In *Proceedings of the 2015 Winter Simulation Conference, December 6–9, 2015, Huntington Beach, CA*, edited by L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, and M. D. Rossetti, 1924–1935. Piscataway: IEEE.

Clausen, U., D. Diekmann, J. Baudach, and M. Pöting. 2015. “Mathematische Optimierung und Simulation von Paketsortieranlagen – Bessere Lösungen durch Kopplung der beiden komplementären Methoden”. In *Simulation in Production and Logistics 2015*, edited by M. Rabe and U. Clausen, 279–288. Stuttgart: Fraunhofer.

Clausen, U., D. Diekmann, and I. Dormuth. 2015. "Impact of different input data sets on the sorting system performance of a parcel transshipment terminal". In *Modelling and Simulation 2015*, edited by M. Al-Akaidi and A. Ayesh, 423–427. Ostend: EUROSIS-ETI.

Clausen, U., D. Diekmann, M. Poeting, and C. Schumacher. 2017. "Operating parcel transshipment terminals: A combined simulation and optimization approach". *Journal of Simulation* 11:2–10.

Deymann, S., and L. Neumann. 2008. "Enterprise Dynamics: TRANSSIM-NODE - A simulation tool for logistics nodes". In *Industrial Simulation Conference 2008*, edited by The European Simulation Society, 283–287. Lyon.

Diekmann, D., J. Baudach, and U. Clausen. 2014. "A new approach of linking mathematical optimization and discrete-event simulation for operating transshipment terminals in the parcel delivery industry". In *Modelling and Simulation 2014*, edited by A. Carvalho Brito, J. M. R. Tavares, and C. Bragança de Oliveira, 254–260. Ostend: EUROSIS-ETI.

Dullinger, K.-H. 2008. *Quo Vadis - Material Handling*. Mönchengladbach: Karten Druck & Medien.

Figueira, G., and B. Almada-Lobo. 2014. "Hybrid simulation–optimization methods: A taxonomy and discussion". *Simulation Modelling Practice and Theory* 46:118–134.

Grasas, A., A. A. Juan, and H. R. Lourenço. 2016. "SimILS: A simulation-based extension of the iterated local search metaheuristic for stochastic combinatorial optimization". *Journal of Simulation* 10:69–77.

Gutjahr, W. J., and A. Pichler. 2016. "Stochastic multi-objective optimization: A survey on non-scalarizing methods". *Annals of Operations Research* 236 (2): 475–499.

Juan, A., and M. Rabe. 2013. "Combining Simulation with Heuristics to solve Stochastic Routing and Scheduling Problems". In *Simulation in Produktion und Logistik 2013*, edited by W. Dangelmaier, C. Laroque, and A. Klaas, 641–650. Paderborn: Heinz-Nixdorf-Inst. Univ. Paderborn.

Jung, J. Y., G. Blau, J. F. Pekny, G. V. Reklaitis, and D. Eversdyk. 2004. "A simulation based optimization approach to supply chain management under demand uncertainty". *Computers & Chemical Engineering* 28 (10): 2087–2106.

Ladier, A.-L., and G. Alpan. 2016. "Robust cross-dock scheduling with time windows". *Computers & Industrial Engineering* 99:16–28.

Ladier, A.-L., G. Alpan, and A. G. Greenwood. 2014. "Robustness evaluation of an integer programming-based cross-docking schedule using discrete-event simulation". In *IIE Annual Conference and Expo 2014*, edited by Institute of Industrial and Systems Engineers, 587–596. Montréal.

McWilliams, D. L. 2005. "Simulation-based scheduling for parcel consolidation terminals: A comparison of iterative improvement and simulated annealing". In *Proceedings of the 2005 Winter Simulation Conference*, edited by M. E. Kuhl, N. M. Steiger, F. B. Armstrong, and J. A. Joines, 2087–2093. Orlando: Omnipress.

McWilliams, D. L. 2009. "Genetic-based scheduling to solve the parcel hub scheduling problem". *Computers & Industrial Engineering* 56 (4): 1607–1616.

McWilliams, D. L. 2010. "Iterative improvement to solve the parcel hub scheduling problem". *Computers & Industrial Engineering* 59 (1): 136–144.

McWilliams, D. L., and M. E. McBride. 2012. "A beam search heuristics to solve the parcel hub scheduling problem". *Computers & Industrial Engineering* 62 (4): 1080–1092.

McWilliams, D. L., P. M. Stanfield, and C. D. Geiger. 2005. "The parcel hub scheduling problem: A simulation-based solution approach". *Computers & Industrial Engineering* 49 (3): 393–412.

McWilliams, D. L., P. M. Stanfield, and C. D. Geiger. 2008. "Minimizing the completion time of the transfer operations in a central parcel consolidation terminal with unequal-batch-size inbound trailers". *Computers & Industrial Engineering* 54 (4): 709–720.

Schumacher, C. 2016. *Vergleich heuristischer Verfahren zur operativen Planung und Steuerung einer Paketumschlaganlage*. Master thesis, Technische Universität Dortmund, Dortmund.

Schumacher, C., M. Poeting, J. Rau, and C. Tesch. 2017. "Combining DES with metaheuristics to improve scheduling and workloads in parcel transshipment terminals". In *Metaheuristics: Proceeding of the MIC* *and MAEB 2017 Conferences*, edited by A. Duarte, A. Viana, A. Juan, B. Mélian, and H. Ramalhinho, 720–729. Barcelona: Online.

Schwemmer, M. 2016. *Top 100 der Logistik: Marktgrößen, Marktsegmente und Marktführer : eine Studie der Fraunhofer Arbeitsgruppe für Supply Chain Services SCS*. Ausgabe 2016/2017 ed. Hamburg: DVV Media Group GmbH.

## AUTHOR BIOGRAPHIES

**MORITZ POETING** is Researcher at the Institute of Transport Logistics at TU Dortmund University. He holds a B.Sc. and M.Sc. in Logistics from TU Dortmund University. His research focuses on sim-heuristics for logistics terminals, simulation and city logistics. His email address is poeting@itl.tu-dortmund.de.

**CHRISTIN SCHUMACHER** attended TU Dortmund University where she studied business mathematics and obtained her M.Sc. in 2016. She is a Researcher and full-time PhD student at the department of Computer Science at TU Dortmund University. In this context she is member of the DFG Research Training Group "Adaption Intelligence of Factories in a Dynamic and Complex Environment" at TU Dortmund University, doing research in the fields of simulation and mathematical optimization. Her email address is christin.schumacher@tu-dortmund.de.

**JONAS RAU** is a Student Assistant at the Institute of Transport Logistics. He holds a B.Sc. in industrial engineering from TU Dortmund University. His research interests include simulation modeling and analysis, and optimizing the performance of operational processes. His email address is rau@itl.tu-dortmund.de.

**UWE CLAUSEN** is Managing Director of the Institute of Transport Logistics at TU Dortmund University and director of the Fraunhofer-Institute for Material Flow and Logistics in Dortmund (since 2001). He worked in the logistics service industry as European Operations Director at Amazon.com and logistics manager at Deutsche Post DHL. In July 1995 he achieved the title of Dr.-Ing. with his doctoral thesis on transportation network optimization at TU Dortmund University. He is Representative of Fraunhofer within ECTRI European Conference of Transport Research Institutes since 2005 (Member of the board from 2013 to 2016), the Advisory Council of the Association of German Transportation companies (VDV), and the scientific advisory board of the Bundesvereinigung Logistik (BVL) e.V. His email address is clausen@itl.tu-dortmund.de.