*Proceedings of the 2023 Winter Simulation Conference*
*C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.*

# SIMULATION-BASED COST MODELING TO MEASURE THE EFFECT OF AUTOMATED TRUCKS IN INTER-TERMINAL CONTAINER TRANSPORTATION

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## ABSTRACT

Container transports within ports are characterized by mostly manual trucks and many handling operations in relatively small areas. Accordingly, they incur a disproportionately large cost in maritime transport chains. One way to reduce these costs is to use automated trucks in a port-internal transport system. Such systems have only been used on terminals, but not within whole ports. Thus, it is important to determine the design parameters of such transport systems. discrete event simulation is particularly suitable for investigating planned systems and controls in logistics. However, the costs of such systems are usually neglected. Therefore, a simulation-based cost model is used in this study to determine the cost-effectiveness of automated trucking systems. It is shown which factors possess the greatest influence on the cost-effectiveness of port-internal container transports. Furthermore, it can be estimated for the first time which cost savings can be achieved by using automated trucks for port-internal container transports.

## 1 INTRODUCTION

Seaports are the main interfaces in the maritime supply chain. Efficiently storing and handling freight assures the smooth operation of global trade. Thus, it is paramount for seaports to maintain cost-efficient transportation processes with a high level of performance (Tierney et al. 2014). Compared to 1998, global containerized trade has tripled. In 2021, the volume was 160 million Twenty-foot Equivalent Units (TEU) (United Nations Conference on Trade and Development 2021). The size of container ships has also increased (Allianz 2022). This results in a larger number of container ships with larger volumes, but with less calls at ports. In consequence, higher peak loads occur in container and landside handlings, often by truck (Ramírez-Nafarrate et al. 2017). Hence, the terminals and their succeeding processes have to raise their performance. The logistical activities of moving containers between organizational separated entities in a port are called inter-terminal transportation (ITT) (Heilig and Voß 2017). Currently, ITT is carried out manually by a limited number of trucking companies and their drivers. Given the relatively small area of operation in ports, ITT combines a large number of handlings in relation to a short distance of travel. These characteristics make ITT a rather unique system of transport, comparable to the stop-and-go activities in city logistics, but with far larger and heavier goods. The design parameters of ITT systems and the investigation of their performance and costs are already some kind of niche problem in literature (see Section 2). Only a few articles research these systems, despite their importance in the logistical process.

However, current ITT systems are about to change with the introduction of automated driving. Automated vehicles are expected to be a good measure to cut costs and streamline processes of ITT. Some ports already use automated guided vehicles (AGV) in restricted areas and on private roads (Hu et al. 2019), but they have neither been technically ready nor certified for public roads. Automated trucks (ATs) in the sense of our research are understood as vehicles of transport with autonomous functions, which do not require human drivers to perform its driving duties. Actual projects are restricted to prototypes and proofs of concept, as we show in Section 2. However, ATs are expected to increase cost-effectiveness of transportation (Gharehgozli et al. 2017). As of today the technological requirements and the expected cost benefits of ATs for ITT systems are still unknown in current literature of transportation systems. Therefore, the objective of this paper is to identify and evaluate the procedural and technological characteristics of ITT regarding their economic benefits. Two research questions (RQ) are explored to satisfy this research objective:

- RQ1: Which main factors of technology and processes influence the cost-effectiveness of ITT systems?
- RQ2: Which cost savings can be expected from an automated ITT system compared to the current state?

The answers to these questions will add to academic literature through describing how AT will shape the cost-effectiveness of current ITT systems. A simulation-based cost model akin to Wang et al. (2007) is utilized to examine factors and costs, which play and important role for the adoption of AT in ITT systems, see Section 3. The experimental design for evaluating the impact of the factors is depicted in Section 4. Section 5 shows the novel results of the simulation-based cost model. In Section 6 the answers to the research questions and their impact on the adoption of automated ITT are discussed. The paper closes with some concluding remarks and implications for managers of ports and freight forwarders.

## 2 STATE OF LITERATURE

In many grown ports, ITT is principally executed by manual trucks (MTs) on public roads. This often leads to a high volume of traffic in the port, congestion at peak times, and long transport times (Kotowska and Kubowicz 2019; Giuliano and O'Brien 2007). A variety of methods to reduce congestion in ITT have already been investigated in the scientific community. For comprehensive literature reviews readers are referred to Heilig and Voß (2017) and Lange et al. (2017). The explored methods include introducing truck appointment systems at logistical nodes to smooth out congestion over the day (e.g., Huynh et al. 2016; Caballini et al. 2020), improving truck scheduling to consider peak hours (e.g., Shiri and Huynh 2016; Torkjazi et al. 2018), and shifting to alternative modes of transport (e.g., Tierney et al. 2014). In the latter, additionally to rail and inland waterways, alternative transport concepts are developed and analyzed (e.g., Nellen et al. 2020; Zheng et al. 2022). In particular, automated transport systems are seen as a promising solution to relieve port infrastructure (e.g., Heilig and Voß 2017; Rose et al. 2022).

To evaluate new concepts and control mechanisms in ITT, simulation has proven itself as an efficient method (Dragović et al. 2017; Huiyun et al. 2018). Azab et al. (2018) use a simulation-optimization approach to study the effects of collaborative truck appointments at container terminals. Caballini and Sacone (2021) define and simulate various algorithms to manage truck arrivals at container terminals ensuring security standards. Do et al. (2016) use discrete event simulation (DES) to estimate the truck waiting times and crane moving distance on a container terminal and apply a genetic algorithm to minimize the emissions generated by the trucks and cranes. Different approaches to reducing congestion at the terminal gates are evaluated via a simulation study on the use case of Chilean port in Gracia et al. (2017). Wasesa et al. (2021) study the impact of an overbooking reservation mechanism on the operational performance and the greenhouse gas emissions of container terminals with an agent-based simulation model. ITT with MTs are studied with the help of simulation exclusively in the work of Gharehgozli et al. (2017).

To sufficiently assess the feasibility of ATs for ITT, the overall investment and operational costs for a fleet of ATs is to be analyzed. However, the cost aspects are mostly neglected in previous studies or reduced to individual aspects, such as fuel consumption. In contrast, literature shows comprehensive cost assessments of AT fleets on public roads. Here, overall system cost benefits approaches are used to compare different use cases for automation to their manual baseline scenarios (Engholm et al. 2020; Ghandriz et al. 2020a;

Ghandriz et al. 2020b; Andersson and Ivehammar 2019; Kavakeb et al. 2015). Total-cost-ownership (TCO) models are developed to analyze the costs of ATs in different weight configurations describing different aspects of the automated vehicle, process and additional node costs (Engholm et al. 2020; Andersson and Ivehammar 2019). TCO analysis is further conducted to assess the impact of automation on the use of different propulsion technology (Ghandriz et al. 2020a; Ghandriz et al. 2020b). However, the structure of ports can vary significantly from typically analyzed use cases of long-distance trucks. In the context of ports, researchers target to model overall application-specific costs of automated vehicle systems (Kavakeb et al. 2015). To the authors' knowledge, there are no cost models used to increase the level of detail and the informative value of simulation models in the area of ITT. Therefore, this article provides a simulation-based cost analysis approach to analyze the economic benefit of the implementation of ITT using ATs.

## 3 METHOD: SIMULATION-BASED COST MODELING

This paper is based on a somewhat unconventional research approach, which combines a DES model of logistical processes with a cost model for the operation of AT fleets (see Figure 1). The results of the simulation model inform the cost model and provide more accurate estimates of logistical process parameters compared to averaged values. Both models and their interplay are described in this section.

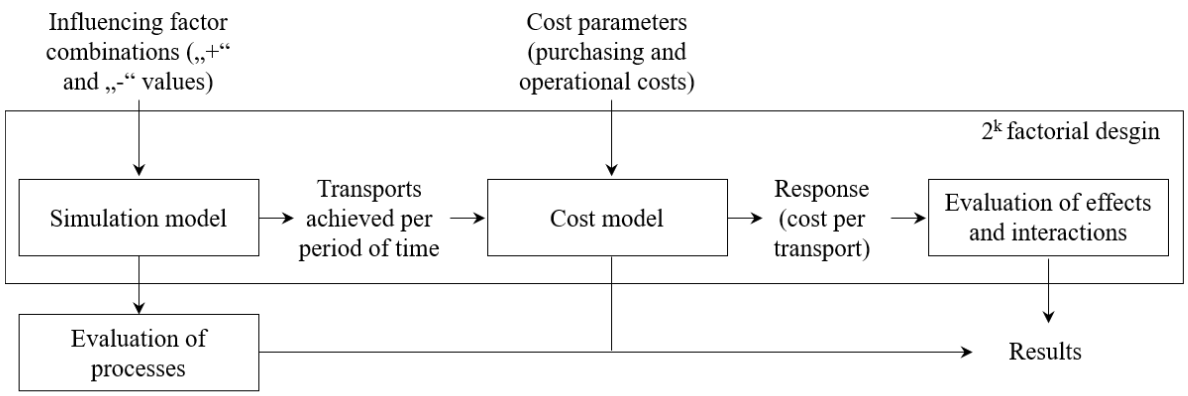


Figure 1: Framework for the simulation-based cost model in a $2^k$ factorial design.

### 3.1 Describing Influencing Factors

Complex transport networks can be characterized by different influencing factors. Table 1 contains selected key factors to describe ITT networks. Technological and process levels were taken into account to assess the impact on the economic benefits of manual and automated ITT systems. According to Section 4, two possible levels (marked with "-" and "+") were determined for each factor.

The first two factors describe the logistics nodes that are connected by the transport system. In this paper, the network of nodes is based on the port of Hamburg and two different numbers of nodes ($n_n$) will be considered. The lower level connects only four separately located container terminals, while the higher one includes 30 actors. Moreover, the transport order data generation between the nodes is randomized, assuming a lower transport volume of an average of $n_{on}$=100 transport orders per included node per day and $n_o$=300 as upper bound, which is roughly derived from Gharehgozli et al. (2017). In addition, three factors describe the ITT system. The first is the number of vehicles. Preliminary studies have shown that under favorable conditions (exclusive roads, few nodes, many orders, and automation) a vehicle completes an average of 27 transport orders per day. However, under poor, contrary conditions, an average of only 14 orders per day. Therefore, a ratio of a vehicle to orders ($r_v$) of 1/27 is assumed as the lower level and 1/14 as the higher level. The "Automation" factor is divided into $f_{trucks}$="automated" and $f_{trucks}$="manual". For the simulation, it is assumed that manual processes have a slightly increased overall susceptibility to errors

Table 1: Factors and selected levels.

| Factors | Levels | |
|---|---|---|
| | - | + |
| Logistics nodes | | |
| Nodes ($n_n$) | 4 | 30 |
| Orders ($n_{on}$) | 100 per node and day | 300 per node and day |
| ITT system | | |
| Vehicles ($r_v$) | 1 for 27 orders | 1 for 14 orders |
| Automation ($f_{trucks}$) | manual | automated |
| Road use ($f_{roads}$) | exclusive | non-exclusive |

in contrast to automated ones, which affect both the travel times and the duration for handling the processes at the logistics nodes. Nowadays, most transports between separately located terminals are carried out on public rather than private infrastructures (Nellen et al. 2020). The factor "Road use" differentiates whether the transports are carried out on exclusive roads ($f_{roads}$="exclusive") for ITT or in mixed traffic ($f_{roads}$="non-exclusive"). Here, transports in mixed traffic are characterized by a higher dispersion based on travel times on weekdays between nodes on non-exclusive roads in the port of Hamburg. On exclusive roads rather optimistic travel times, based on less frequented times at night, are assumed.

### 3.2 Discrete Event Simulation

Tour planning problems of fleets of vehicles are among the hardest combinatorial optimization problems. Even heuristic methods struggle to generate solutions in adequate computation times. Dynamic adaptive vehicle routing or dispatching approaches try to react appropriately to variations during the execution process of transports. Fleischmann et al. (2004) developed an event-based algorithm for a pickup and delivery problem. They consider a dynamic system for real-time routing, which assigns transport orders to a fleet of vehicles according to certain criteria (e. g. information on travel times). In this paper, similar event-driven dispatching rules are applied, whereby extended problem-specific multi-attribute priority rules are used to initiate the allocation of open transport orders to vehicles over time. In order to test methods for dynamic dispatching and to represent variables in the course of the execution process, DES is a suitable method. Tecnomatix Plant Simulation 16 was selected. It is a standard software for the simulation of manufacturing systems and provides modules and functions to support the modeling of transport systems.

A transport order in simulation consists of the pickup and delivery of a container. The model imports a new order list for a weekday for each simulation run. Each transport order is generated by choosing two different logistics nodes at random and setting a release time and due time. An order assignment attempt is initiated by the vehicle at the beginning of a shift, after a driving break, after charging at a charging station, after a short waiting period following a previously unsuccessful order assignment, or when a job has been successfully completed. The order assignment algorithm evaluates all orders not yet selected with respect to two criteria: first urgency and then distance. Orders are assigned to free vehicles. Since it is often beneficial to evaluate travel times instead of distance in route planning problems with time windows, the second criterion of assignment is based on travel time forecasts. In case of several feasible orders with equal urgency (since deadlines are set per hour), the necessary travel time to the source based on current traffic information is crucial. The method developed in this paper additionally estimates whether a transportation order is feasible with respect to the time constraints (at its source and destination) based on the dynamically generated reference travel times and the forecasted traffic conditions. In this way, dynamic influencing factors (e.g., stochastic driving and service times) can be taken into account. The algorithm also considers whether a order is compatible with the driver's break and shift times. If a suitable order is found, it is assigned and execution is initiated. The factors and levels shown in Table 1 are considered in the model. Therefore, we, e.g., consider both ATs and MTs in the simulation model (both as non-combustion engine vehicles). Assumptions were made as to the impact of this on travel times and handling at the nodes based on expert interviews (Table 2). Charging and maximum range of the vehicles are based on state-of-the-art technology in the heavy truck industry. The process times at the nodes were determined as part of a survey that included port stakeholders in the Port of Hamburg. Operation times are based on typical shift models in the German port industry. These times adapted for automated container transport. The routes between the different arrival points are represented in a simplified way as dwell times on model blocks based on dynamic travel time matrices.

Table 2: Simulation model assumptions.

| Parameter description | Symbol | Assumption |
|---|---|---|
| Number of chargers | $n_{charg}$ | approx. one charger for 20 vehicles |
| Max. range of the vehicles | $d_r$ | 400 km |
| Charging time | $t_c$ | approx. 4 s per km |
| Processing time at nodes | $t_p$ | triangular distributions (MTs: c=1,500 s, a=900 s, b=3,600 s; ATs: c=1,200 s, a=900 s, b=1,500 s) |
| Driving times/ breaks | $t_b$ | MTs: after 4.5 hours an approx. 45 min break |

### 3.3 Cost Model

To estimate the resulting costs of different automation levels, road usages and node networks a comprehensive cost model for purchasing and operational costs was developed. Purchasing costs include investments in the vehicle system, its installation, and infrastructure measures. Operational costs summarize recurring payments for energy costs, maintenance, staff (e.g., safety driver or control center), general administrative costs, tax, and insurance costs. Relevant cost parameter estimations are listed in Table 3. All cost parameters for ATs and MTs as well as the required infrastructure are based on expert interviews from the heavy-duty truck industry. Relevant cost parameters for building port road infrastructure are from the Hamburg Port Authority. The model describes the overall costs per transport (CPT) including the initial investment $I_0$, all relevant purchasing and operational cash flows $F_t$ divided by the total amount of transport orders per year $n_O$ over a time period of usage period of $T = 15$ years (see formula 1). Here, the amount of fulfilled transport orders simulated in the port serves as cost model input.

$$CPT = \frac{I_0 + \sum_{t=1}^{T} F_t}{n_o \cdot T} \tag{1}$$

The initial investment $I_0$ includes the vehicle and system investment, required infrastructure measures such as possible dedicated roads and charging infrastructure with the required amount of vehicles $n_v$ and their purchasing price for vehicles $I_v$ and chassis $I_C$, the distance of dedicated road network $d_{net}$ and the amount of installed chargers $n_{charg}$. For vehicles, purchasing cost for automated solutions $I_{va}$ and manual solutions $I_{vm}$ are applied as $I_v$. Infrastructure costs are applied with cost factors for the road $c_{road}$ and costs per charger $I_{charg}$. Installation, deployment, and overall project costs are summarized by $c_{inst}$.

$$I_0 = n_v \cdot (I_v + I_c) + d_{net} \cdot c_{road} + n_{charg} \cdot I_{charg} + c_{inst} \tag{2}$$

$F_t$ summarizes all procurement expenditures occurring in a particular year of operation. It is categorized in an investment of capital $I_t$ and operational expenses $O_t$ for the system (see formula 3). Following (Kavakeb et al. 2015), the annual operating cash flow is discounted with an inflation rate of $i = 2$ %, which is the official inflation target over medium term (European Central Bank 2021). After that, the present value of the cash flow is calculated using a risk-adjusted discount rate of $r = 5$ % (Kavakeb et al. 2015).

$$F_t = (I_t + O_t) \cdot \frac{(1+i)^t}{(1+r)^t} \tag{3}$$

Table 3: Cost model parameters.

| Parameter description | Symbol | Unit | Value | RP |
|---|---|---|---|---|
| Costs vehicle manual | $I_{vm}$ | €/ vehicle | 140,000 | 10 |
| Costs vehicle automated | $I_{va}$ | €/ vehicle | 175,000 | 10 |
| Costs chassis | $I_c$ | €/ chassis | 25,000 | 10 |
| Costs charger | $I_{charg}$ | €/ charger | 375,000 | 15 |
| Costs dedicated road | $c_{road}$ | €/ km | 2,400,000 | 15 |
| Installation costs | $c_{inst}$ | € | 5,000,000 | - |
| Maintenance costs vehicle | $m_v$ | €/ km | 0.117 | - |
| Vehicle tax | $t_v$ | €/ year | 550 | - |
| Vehicle insurance | $i_v$ | €/ year | 800 | - |
| Costs electricity | $c_{el}$ | €/ kWh | 0.2 | - |
| Maintenance costs chassis | $m_c$ | €/ chassis | 250 | - |
| Costs safety driver | $c_{sdm}$ | €/ sd | 60,000 | - |
| Costs technical supervision | $c_{sda}$ | €/ sd | 80,000 | - |
| General costs per transport | $c_g$ | €/ transp. | 11 | - |
| Energy consumption vehicle | $u_v$ | kWh/ km | 1.26 | - |
| Calculation period | T | Years | 15 | - |
| Inflation | i | % | 2 | - |
| Risk adjusted discount rate | r | % | 5 | - |
| Number of vehicles | $n_v$ | Quantity | Input | - |
| Number of chargers | $n_{charg}$ | Quantity | Input | - |
| Driven distance | $d_v$ | km | Input | - |
| Distance road road network | $d_{net}$ | km | Input | - |
| Number of yearly orders | $n_o$ | Quantity | Input | - |

Invests of capital $I_t$ consist of vehicle procurement payments including chassis after an operation period of 10 years. The annual cash flow for operational costs consists of annual costs operating the vehicle system itself ($O_v$) and costs for operating and maintaining the dedicated road and charging infrastructure ($O_{Infr}$).

$$O_t = O_v + O_{Infr} \tag{4}$$

The vehicle operation costs are composed of insurance and taxes, electricity costs, maintenance, and general costs (see (5)). The costs for coordination and control of the vehicles are represented by the safety driver costs ($c_{sd}$). Energy and maintenance costs are calculated by total driving distance of the vehicles ($d_v$). For energy costs, the electricity price ($c_{el}$) and the energy consumption ($u_v$) are used. For maintenance a general costs parameter ($m_v$) is applied. Insurance ($i_v$), taxes ($t_v$), safety driver costs ($c_{sd}$) are implemented as costs per vehicle. General administrative costs ($c_{gen}$) are calculated per order.

$$O_v = n_v \cdot (i_v + t_v + c_{sd} + m_c) + d_v \cdot ((n_v \cdot u_v) + m_v) + n_o \cdot c_g \tag{5}$$

Due to scenarios of different levels of automation, the cost rates for assessing the cost of a safety driver vary. The safety driver costs per vehicle are calculated based on a 24-hour shift model, 360 operating days per year, and 210 working days per employee and year. For MTs, the assumption is the annual staff costs for a regular truck driver ($c_{sdm}$). The safety driver remains in the truck cabin to operate it. The costs for safety drivers, who work remotely in the control center to control a certain amount of ATs, are not yet known due to the novelty of the technology. It is assumed that operating advanced technology requires a higher qualification or degree than manual driving. Therefore, the costs for a technical supervisor are adapted ($c_{sda}$). It can be assumed that the technical supervisor for automated vehicles operating from a control center is able to monitor several vehicles at the same time. Following (Engholm et al. 2020), a number of simultaneously supervised vehicles $n_{sva} = 10$ is assumed. Accordingly, the number of simultaneously supervised vehicles for a MT of $n_{svm} = 1$ is assumed.

$$c_{sd} = \begin{cases} c_{sd} = 360/210 \cdot 3/n_{svm} \cdot c_{sdm} & \text{:manual} \\ c_{sd} = 360/210 \cdot 3/n_{sva} \cdot c_{sda} & \text{:automated} \end{cases} \tag{6}$$

Annual infrastructure costs refer to the operation and maintenance of the required roads for exclusive road use as well as the operation of the charging points to be installed. For the annual costs of the charging infrastructure, a flat rate of 10 % procurement costs are calculated. According to expert assessments from port authorities the road maintenance costs are calculated analogously. To calculate individual scenarios with different factor characteristics regarding automation, individual parameters and their cost rates are varied. Furthermore, different vehicle prices apply for the vehicle types "manual" and "automated". In addition to the cost parameters and individual boundary data of the levels, the results of the ITT-system simulation are used to calculate the required number of vehicles ($n_v$), the number of orders fulfilled ($n_o$) and the mileage of the vehicles ($d_v$). The simulation results of an operating day are scaled to the operation of a year with 350 operating days and calculated for a system runtime of 15 years. These quantitative considerations complete the cost model of the research methodology.

## 4 DESIGN OF EXPERIMENTS

Several factors potentially have an influence on the efficiency of ITT systems, as presented in Section 3. It is assumed that the factors strongly influence each other, which implies that different factor combinations also might have an impact on the efficiency of the transport system. To reduce the number of factors to be considered and take their respective influence into account, a factor screening with a $2^5$ factorial experimental design based on (Law 2014) was conducted. Two expressions per factor were considered, as presented in Section 3. The lower level is symbolized with a "-" and the higher one with a "+". We assume that the response is approximately linear. For further studies, this has to be thoroughly tested. This approach resulted in 32 design points with a different combination of factors each. For every design point, the simulation was run 50 times each due to its high stochasticity. The results were transferred to the cost model for evaluation. The median of the overall costs per transport (CPT) over all 50 runs of a design point was used to calculate the response value for the simulation-based cost model. In addition to the operational costs, the CPT include the investment costs for the vehicles and the infrastructure. The resulting design matrix with the 32 design points and the corresponding responses in € is shown in Table 4.

The design matrix can be used to calculate the effects of the factors on the responses. The respective effects of the five investigated factors show how the CPT changes when one factor is varied from low to high. These cost values are denoted by $e_j$ for factor $j$ and can be calculated by subtracting the average CPT per factor of design points with a low level ("-") from the average costs with a high level ("+"). Therefore, the effect of the factors can be understood directly as a change in CPT, $\Delta$ CPT, in €. Furthermore, the design matrix enables the analysis of the interactions between different factors. These interactions display if the effect of one factor $j_1$ depends in some way on the level of some other factor $j_2$ or vice versa. The measure of the interaction is denoted as $e_{j_1 j_2}$. It is calculated as the difference between the average CPT when the factors 1 ($j_1$) and 2 ($j_2$) have the same level (both "+" or both "-") and the average CPT when they show different levels. If the interaction $e_{j_1 j_2}$ is positive, the two factors influence each other positively when having different levels. Consequently, if the value of interaction is negative, the two factors influence each other positively when having the same levels (Law 2014). Since the evaluation of the interaction should rather be understood as the degree of influence, a normalized value was also given here. For this purpose, the value of the highest interaction was assumed to be 100 % and the other values were set in relation to it. The identified effects and interactions of the five factors studied are presented in Table 5. They provide the basis for the presentation and further interpretation of the results in Sections 5 and 6.

## 5 RESULTS

To investigate the impact of ATs on ITT, different factor combinations were studied. The first step of the chosen $2^5$ factorial experimental design was to analyze the effects of the individual factors. The CPT in € was chosen as the main response value of the simulation-based cost model and can be seen in Table 4.

Table 4: Design matrix of the $2^5$ factorial design.

| | Logistics Nodes | | ITT System | | | Results | |
|---|---|---|---|---|---|---|---|
| Des. point | Nodes ($e_1$) | Orders ($e_2$) | Vehicl. ($e_3$) | Autom. ($e_4$) | Road use ($e_5$) | Response [CPT in €] | Fulfillment rate [ %] |
| 1 | - | - | - | - | - | 128.21 | 59.1 |
| 2 | + | - | - | - | - | 80.46 | 58.6 |
| 3 | - | + | - | - | - | 82.48 | 58.2 |
| 4 | + | + | - | - | - | 66.49 | 58.9 |
| 5 | - | - | + | - | - | 107.75 | 99.9 |
| 6 | + | - | + | - | - | 78.88 | 100.0 |
| 7 | - | + | + | - | - | 80.07 | 100.0 |
| 8 | + | + | + | - | - | 69.85 | 100.0 |
| 9 | - | - | - | + | - | 21.24 | 97.7 |
| 10 | + | - | - | + | - | 18.66 | 96.8 |
| 11 | - | + | - | + | - | 18.55 | 97.9 |
| 12 | + | + | - | + | - | 18.12 | 98.7 |
| 13 | - | - | + | + | - | 27.74 | 100.0 |
| 14 | + | - | + | + | - | 25.24 | 100.0 |
| 15 | - | + | + | + | - | 25.45 | 100.0 |
| 16 | + | + | + | + | - | 23.58 | 100.0 |
| 17 | - | - | - | - | + | 130.17 | 58.2 |
| 18 | + | - | - | - | + | 81.72 | 57.5 |
| 19 | - | + | - | - | + | 83.60 | 57.2 |
| 20 | + | + | - | - | + | 67.54 | 57.8 |
| 21 | - | - | + | - | + | 107.71 | 99.6 |
| 22 | + | - | + | - | + | 78.87 | 99.9 |
| 23 | - | + | + | - | + | 80.06 | 99.9 |
| 24 | + | + | + | - | + | 69.80 | 100.0 |
| 25 | - | - | - | + | + | 21.52 | 95.1 |
| 26 | + | - | - | + | + | 18.77 | 94.5 |
| 27 | - | + | - | + | + | 18.76 | 95.3 |
| 28 | + | + | - | + | + | 18.32 | 95.7 |
| 29 | - | - | + | + | + | 27.73 | 100.0 |
| 30 | + | - | + | + | + | 25.18 | 100.0 |
| 31 | - | + | + | + | + | 25.46 | 100.0 |
| 32 | + | + | + | + | + | 23.56 | 100.0 |

The CPT values vary widely depending on factor combination of the respective design point, ranging from 18 € to 130 €. It is noticeable that all design points, which are characterized by a high degree of automation (9 to 16 and 25 to 32), show a proportionally lower CPT value in comparison to design points with manual vehicles. The effects of the different factors can be found in the left two columns of Table 5.

Table 5: Effects and interactions of factors.

| Effects | | Interactions | | |
|---|---|---|---|---|
| No. | Δ CPT [€] | No. | Absolute | Normalized |
| $e_1$ | -13.84 | $e_{12}$ | 6.70 | 55.96 |
| $e_2$ | -13.01 | $e_{13}$ | 2.96 | 24.78 |
| $e_3$ | 0.15 | $e_{14}$ | 11.96 | 100.00 |
| $e_4$ | -64.74 | $e_{15}$ | -0.06 | -0.53 |
| $e_5$ | 0.38 | $e_{23}$ | 2.85 | 23.84 |
| | | $e_{24}$ | 11.23 | 93.83 |
| | | $e_{25}$ | -0.06 | -0.51 |
| | | $e_{34}$ | 6.10 | 51.03 |
| | | $e_{35}$ | -0.06 | -0.52 |
| | | $e_{45}$ | -0.29 | -2.39 |

$e_1$ represents the effect of nodes, $e_2$ the effect of orders, $e_3$ the effect of number of vehicles, $e_4$ the effect of automation and $e_5$ the effect of road use. Automation $e_4$ shows the highest negative value of 64.74 Δ CPT. Thus, a high degree of automation of the vehicles reduces the transportation costs by an average of 64.74 € per order. Furthermore, many nodes ($e_1$) as well as a high number of orders ($e_2$) reduce the CPT of the ITT system. The use of exclusive roads ($e_5$) shows almost no effect on CPT of the model. The evaluation of the individual parameters shows that the number of vehicles ($e_3$) has no appreciable effect on the CPT. Another important process parameter is the fulfillment rate of all orders per design point. Looking at Table 4, it can also be seen that the rate of completed orders varies greatly among the experiments. In the design points 1 to 4 and 17 to 20, not even 60 % of the planned orders are fulfilled. In these design point, only a few non-automated vehicles were used. Whereas in the other design points an order fulfillment rate of more than 90 % was achieved. The order fulfillment rate in the design points 13 to 16 and 29 to 32 is close to 100 %, with no large scatter in the results. In all these design points, many ATs were used. Without taking the order fulfillment rate into account on the cost side, the results from design points with very low and with very high order fulfillment rates should be handled with care.

In the second step, the interactions of two factors were calculated and analyzed. If the interaction is positive, then effects with the same sign are predominant. Opposite levels are to be selected for a reduction of the costs. If the value of the interaction is negative, the cost can be reduced by choosing the same level of effects. A higher absolute value signifies a greater interaction of effects (see Table 5). This study shows that not all parameters influence each other to the same extent. Thus, only the four interactions with the highest absolute values are presented. It has already been seen that a high degree of automation always leads to a reduction in CPT. However, if the system is less automated, a high number of nodes, as well as many orders can bring cost advantages. This relationship can be seen in the interactions $e_{14}$ and $e_{24}$ (see table 5). In highly automated systems, fewer vehicles are needed (interaction $e_{34}$). Conversely, this means that more vehicles are needed in manual systems. Finally, both a high number of nodes and many orders lower the CPT ($e_{12}$). Based on the results, the cost-effectiveness of AT in ITT can be evaluated.

## 6 DISCUSSION

This section discusses the results of this research and presents some interpretations for future developments of ITT systems for ports. A number of influence factors on the cost-effectiveness of ITT systems is identified to answer research question one. The main factor of influence on the cost of ITT systems is the deployment of ATs. Automating means of transportation reduces costs of ITT, because the required staff is obviously lower than with MTs. This plays a particular role for smaller ports with fewer actors, when the share of labour costs is relatively high per transport order. Hence, smaller ports need only few ATs to lower their CPT. This effect of cost reduction is moderated for larger ports. More logistical nodes and more transport orders align the effect of ATs on CP in comparison with MTs. Hence, CPT of MTs are also expected to decrease with the size of the system. This implies the existence of scaling effects also for ITT systems. Although this might be expectable for all transportation processes, one should note that ITT systems with ATs might scale easier than with MTs. A potential reason is that ATs can conduct transports as long as necessary, given the availability of propulsion energy. However, truck drivers have to adhere to a maximum of working hours, which limits the capacities and reduces the scaling potential of MTs. Nevertheless, CPT of systems with ATs are always lower than in systems with MTs. Altogether, it can be said that the use of ATs is expected to result in lower CPT of ITT systems with consideration of the size of the system.

This leads to the second research question, how much cost savings can be expected from the use of ATs for ITT. The impact of the number of nodes, orders, vehicles and exclusive roads is secondary in comparison to the use of ATs as such. The span of costs of all design points with ATs ranges from 27.4 € (No. 13 in Table 4) to 18.12 € (No. 12 in Table 4). The minimum costs can be achieved when ATs are combined with a large, efficient and encapsulated ITT system with many nodes and orders. This requires a well-balanced number of efficiently used vehicles, which can satisfy the whole workload with neither creating idle vehicles nor long waiting times for containers transports. This implies that some of design points in Figure 3 are not efficient, because of too low order fulfillment rate (design points around 60 %). At the same time, an order fulfillment rate of 100 % points at a too low number of vehicles, which results in an insufficient performance of the overall system to process all orders. One should note that unfulfilled orders have not been penalised in this research. Design points with an order fulfillment rate between 100 % and 90 % are seen as realistic in this scenario (design points 9 to 13 and 25 to 29). The existence of exclusive roads is not important, because the costs for ATs in mixed traffic is only slightly higher (see for example No 28. in Table 4). The average costs of all design points (No. 1 to 8 and 17 to 24 in Table 4) with MTs are 87.10 €, while the average costs with ATs are 22.36 € (No. 9 to 16 and 25 to 32 in Table 4). So, the difference between design points with ATs and design points with MTs is 64.74 €. This seems plausible because the average price of a transport with a MT within the port of Hamburg is between 60 € to 80 € according to our personal experience. Hence, it is expected that the use of ATs for ITT is going to reduce the costs per transport by around 60 % to 75 % in the future.

## 7 CONCLUSION

This study investigates the impact of technological and procedural characteristics on the economics of ITT systems. It is investigated which cost reduction costs can be expected from the introduction of ATs. A simulation model in alignment with a European port has been used to inform a cost model of an ITT system. The influence of five factors is analyzed: (1) number of logistical nodes, (2) number of orders, (3) number of transport vehicles, (4) degree of automation of the vehicles, and (5) the use of exclusive roads. The factors are combined in $2^5$ factorial design, which ended up in 32 design points. Each design point stands for a unique combination of factors and is used to quantify the factors' effects. The effect of each combination is expressed as costs per transport. This describes the cost impact of each factor. Furthermore, the influence of factors on each other is also investigated. The results show that ATs will most likely be superior to MTs in terms of costs of ITT systems. Other factors can moderate this cost benefit of ATs, such as systems with many nodes. Altogether, it is expected that costs of transportation will decrease by over 60 % with the introduction of ATs. This study is the first, which systematically quantifies the potential reduction of costs expected from the use of ATs in ITT systems. However, this study still contains several limitations. Firstly, we did not take penalty costs for not processed transports into consideration. It is expected that deliveries have to arrive at their destination at some point in the future. Usually, trucking companies often have around three days to finish the transport. If it is further delayed, there will be some kind of penalty costs. This creates a bias towards design points with fewer vehicles, which are fully utilized. However, the impact of this bias is not considered as very strong, because the influence of the number of vehicles on the overall costs of transportation is not that big in the cost model. Secondly, the input data of the simulation has been limited to a certain period of time. The economic development of ports differs across places and changes over time. Thirdly, the degree of automation in this study is assumed to be manual or automated. In practice, different levels of autonomy of trucks and cars are expected. Some automated functions might be more important than others and contribute more to the cost-effectiveness of a vehicle. Most important is the removal of a human as a safety driver. Altogether, it can be said that ATs will have serious impacts on transportation. This counts also for ITT systems, which have a special position in the logistical chain. Further research on automation in transportation is needed in order to validate and verify the results of this study and expand on the academic body of ITT systems.

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