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Implementation of a Simulation Environment for Electrified Heavy Duty Vehicles in a Logistics System

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Summary

The intention of the work described in this paper is to enable the evaluation of fleets of specialized electrified heavy-duty vehicles in the use case of logistics systems in ports from an economical and ecological point of view. The concept is to combine different simulation environments to support the component design of the vehicle and the infrastructure layout in the development phase to ensure a capable vehicle fleet and prevent component overdimensioning.

Keywords: fleet, heavy-duty, infrastructure, port, special vehicles

1 Introduction

Ocean shipping is a major pillar of the global economy. Approximately 90 % of the world's goods are transshipped by water. Since the 1960s, container shipping has developed into the dominant technology in liner shipping and today defines the standard in the field of seabound general cargo transport. [1], [2], [3]

Within ports, containers are transported with purpose-built heavy-duty vehicles. Vehicles most frequently used for this task are terminal tractors. Since these vehicles nowadays are propelled mainly by a diesel-powered drivetrain, they account for a large proportion of a port's pollutant and noise emissions. [4]

Stricter regulations regarding these emissions drive the transition towards alternative propulsion technology for terminal tractors. The main challenge of the electrification of commercial vehicles is to provide a high vehicle availability at low additional costs compared with conventional technology. Due to the high price of electrical energy storages, this implies the demand for rightsizing of the components on vehicle and infrastructure side. [4]

Addressing these challenges requires a holistic investigation method. The combination of logistics and vehicle simulation offers a huge optimization potential in terms of vehicle electrification dimensioning, overall fleet composition and infrastructure equipment investment. Furthermore, electric vehicle operations improve with tailor made operation strategies considering the logistics process from an energetic point of view. These are part of this paper.

2 Methodology

The general simulation concept is separated into three parts. First, an environmental simulation of the specific use case is built. Second, a longitudinal dynamics simulation is set up to enable an energetic evaluation of the use case. Lastly, a purpose-built simulation environment for managing the entire vehicle fleet is set up to evaluate possible vehicle and fleet configurations.

2.1 Environmental Simulation

Main use of the environmental simulation is to generate all possible velocity profiles of the specific use case in advance. This is realised by implementing a model of the use case in the traffic simulation software “Simulation of Urban MObility” (SUMO) [5].

A road network of the use case is created according to methods proposed by Lopez et al. [6] and Dingil et al. [7]. Main parts of the use case are mapped in Open Street Maps (OSM). The basic network creation is done by importing a section of the digital map into the network editor of SUMO. Next, the elements of the network irrelevant for the investigation are removed. Advantages of this import approach are: Firstly, the correct mapping of the main roads inside the port including existing junctions and driving directions. Secondly, the network coordinates resemble the correct GPS coordinates.

In this network, a set of Points of Interest (POIs) is defined. The dataset contains every location the terminal trucks can drive to, including possible container pick-up and drop-off positions, parking positions and the location of the charging infrastructure. For the POI definition, a set of simplifications apply: Every eight adjacent loading positions are summarized to one position in the network to reduce the number simulations to run. Further, the turning manoeuvre of the tractor is neglected and additional traffic in the port is not considered.

The traffic simulation offers a number of driver models, which derive a velocity profile from environment parameters listed above. For the purpose of the investigation at hand, the “Intelligent Driver Model” (IDM) based on the “Optimal Velocity Model” (OVM) is chosen. The model is able to represent realistic driving behaviour despite the lack of additional traffic in the network. [8], [9], [10] The acceleration capability of the vehicle is one of the input parameters into the IDM. The reduction of the acceleration capability needs to be taken into account, to ensure, that the velocity profile complies with the vehicles performance capabilities. This is achieved with the correlation shown in the figure below.

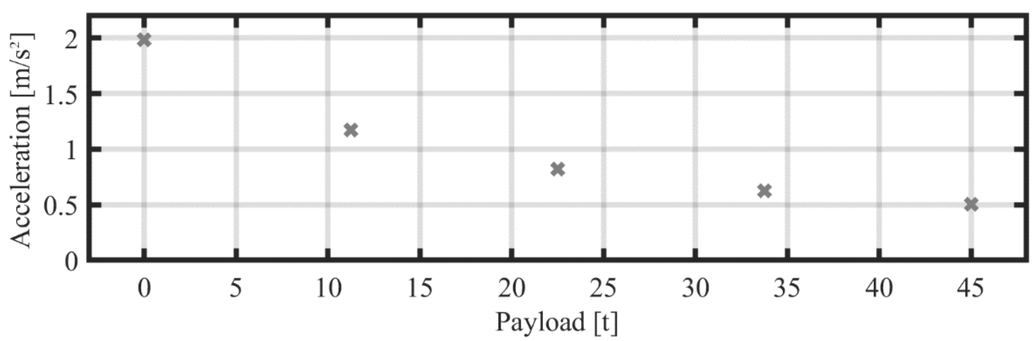

Figure 1: Acceleration ability depending on vehicle payload

The acceleration ability varies from 2.0 m/s² without any payload to 0.5 m/s² at the maximum considered payload of 45 t for this use case. The mission profiles are routed as the shortest connections from one POI to another for all implemented POIs. An automated call of the built-in routing algorithm in SUMO for all possible missions between the POIs is implemented.. These profiles with their respective GPS trace for every possible route and payload serve as input for the longitudinal dynamics simulation.

2.2 Vehicle Simulation

The vehicle missions derived from the environmental simulation, described in the previous section, consist of both payload and speed profile. The purpose of the longitudinal dynamics simulation is to derive the vehicle energy demand and respective depletion of battery state of charge for each transport mission, as well as for the intermediate relocation service trips and charging events. Lateral dynamics are neglected, as these are already considered in the design of the velocity profile by SUMO which takes curvature into account. The tractive force demand at the wheels is calculated based on driving resistance parameters, speed, acceleration and inclination. Additional demands are considered by defining time dependent auxiliary loads in the model. These cover conditioning demands for the driver's cabin, hydraulics for coupling and uncoupling of trailers as well as additional static power demands.

The vehicle powertrain is modelled based on modularly connected subsystems representing drivetrain components. In the figure below, the top-level structure of the simulation model is shown:

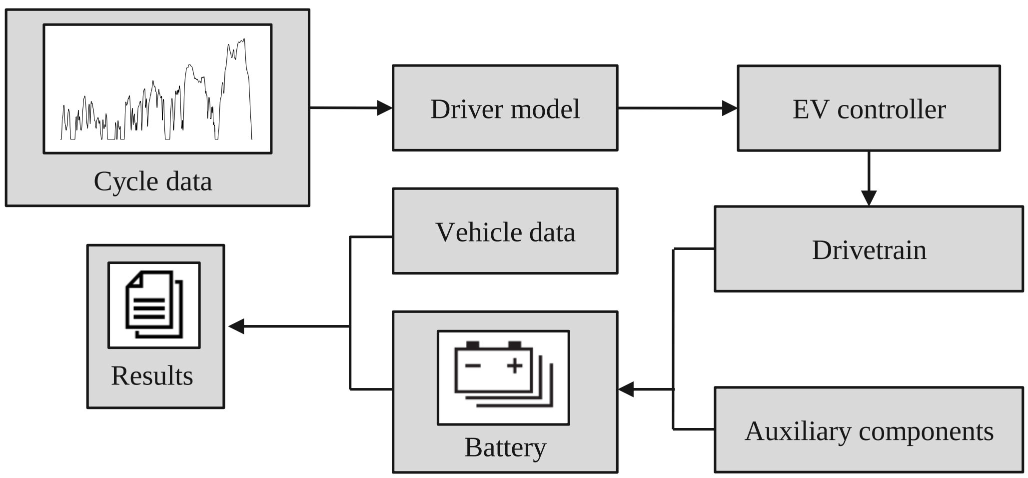

Figure 2: Schematic top level of the vehicle simulation

The components are either energy storages or converters. Both electrical and mechanical physical domains are considered. The internal structure is either based on equation systems describing the physical behaviour or implemented as lookup tables representing the component losses. The initial parameterization shown in the following table is based on datasheets of the specific or similar components.

Table 1: Initial parameterization of the vehicle simulation

	Value
Vehicle mass	11.5 t
Rolling resistance coefficient	0.008
Drag coefficient · vehicle frontal area	2.25 m^2
Final drive efficiency (constant)	82.5 %
Auxiliary power consumption (constant)	3.5 kW

Where applicable, these parameters are scaled to the use case. The modular design of the model represents the real structure of the components with the respective interfaces. Signal traces of the system states can easily be derived for simplified calibration of the model with measurement data. This serves as a validated base for further investigations. For each simulation run, feasibility of the mission generated with SUMO, in terms of vehicle performance, is double-checked by observing the simulation results. In addition, time-dependent and cumulative behaviour, such as charging power, state of charge of the battery, thermal and derating behaviour are simulated and can be considered for further investigations. Iterative simulations are carried out for vehicle component dimensioning. Data handling efficiency is achieved by extracting key performance indicators such as the energy demand for each trip. The figure below shows the energy demand distribution of trips in the use case.

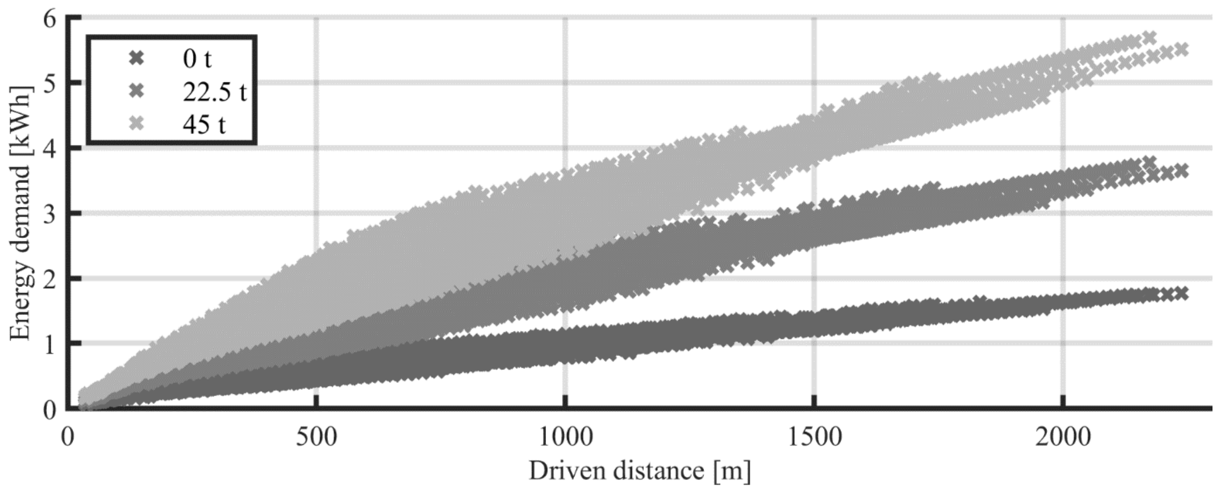

Figure 3: Energy demand over driven distance depending on varying payloads

From the figure it can be seen, that single missions, defined as container transport or relocation, have a maximum length of 2.5 km. Energy demand strongly depends on the payload and more than doubles between empty and fully laden trips. This gives an indication, that the sequence of multiple trips, covered by a single battery charge, or vice versa, the planning of intermediate charging events, is key factor for the implementation of electrification. Therefore, these key performance indicators are simulated in advance for all trips and appended to the simulation dataset, which serves as input into the final element of the simulation environment described in the next section.

2.3 Logistics Simulation

One major economical goal of logistics is efficiency, meaning to reduce costs to a minimum and simultaneously improve the performance of a system. At the same time, ecological goals are becoming increasingly more important for logistics. The efficiency of a logistics system is evaluated based on four criteria. First, the delivery time, i.e. how much time is required from materials planning to provision of the logistical object, is a measure of this system. The second criterion, the delivery reliability, refers directly to the delivery time and is a measure of how well the agreed delivery time corresponds to the actual delivery time. In addition, the criteria delivery quality and delivery service are measures of a logistics system. Delivery quality describes in which condition the logistical object arrives at its destination. The term delivery service includes various additional services outside the actual transport of a logistical object. [11], [12], [13], [14]

The environmental objectives of logistics systems are defined as the minimisation of energy consumption, space requirements, pollutant emissions, noise and waste by the system. The consequences of economical and ecological objectives are generally contradictory and must be weighed against each other. [15]

The technical approach of discrete event simulations (DES) is used to simulate logistics systems in a detailed manner, as shown by Legato et al. [16] or Tako et al. [17]. Main advantage of this type of simulation is the high computational efficiency due to a smaller amount of simulation steps compared to a discrete time simulation (DTS). The main purpose of the methodology described in this paper is to enable a detailed energetic evaluation of electrified vehicle fleets and their infrastructure in a port. For this reason, the DTS approach is chosen, despite the advantages of a DES concerning the calculation efficiency.

Input for the logistics simulation is a logistics plan containing the information of the goods that are to be transported in the logistics system, in addition to the previously mentioned partial results of environmental and longitudinal dynamics simulation. In a container terminal, this plan contains an entry for every container to be transported with a given set of parameters to enable the evaluation by the algorithms of the logistics system. An example parameter set for one container is shown in the table below.

Table 2: Exemplary set of parameters for one container

Parameter	Value
Time of provision	2300 sec
Unique container ID	0025
Mass	14 t
Pick-up position ID	140001
Drop-off position ID	210003

The overall purpose of this combined simulation is the investigation of the main vehicle and fleet parameters as well as the setup of the charging infrastructure. Configurable parameters are the number of vehicles in the fleet and the respective nominal battery energy content of each vehicle. The maximum charging power of the vehicle's battery depends on the battery's SOC. Due to the fact, that the charging process is simulated in the logistics simulation, a battery model containing information about the power limits of the battery is used. The Depth of Discharge (DOD) of the battery can be set to define the usable battery energy content. Initial values are an upper limit of 90 % State of Charge (SOC) and a lower limit of 15 % SOC, resulting in a DOD of 75 %, which is seen as an estimation to the safe side. On infrastructure side, the number of charging stations and the deliverable battery charging power of one charging station are configurable. The location of the charging position is also interchangeable, but not in the scope of the work presented in this paper.

2.4 Simulation procedure

In the following section, the operations executed at each simulation time step are described. The simulation setup runs with a step size of one second for a total duration of 24 h. The following figure represents the simulation procedure of a single time step.

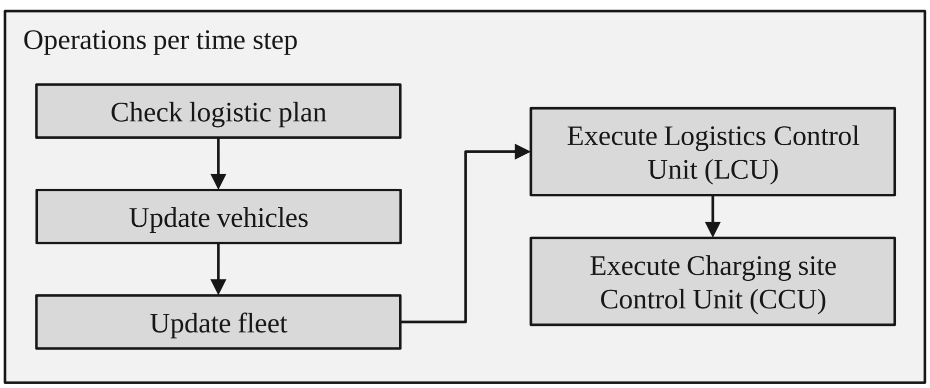

Figure 4: Flow chart of the logistics simulation process

At the beginning of each time step, the logistics plan is checked for new containers available. If necessary, the parameters of each vehicle are updated. Modified parameters are: the current position of the vehicle, the identification of the container currently loaded, the route of the vehicle and the payload. Based on this set of parameters and the previously calculated simulation results, the battery power at this time step is determined. At this point, the varying auxiliary power consumption depending on the current mission of the vehicle is also considered to account for the energy demand of the hydraulic and pneumatic systems of the vehicle. If the traction battery of the vehicle is currently being charged, a value range check for the charging power is executed according to a proprietary battery model to ensure that the SOC-dependent power limits of the battery are not violated. With this value for the updated battery power, the updated SOC of the vehicle is calculated. Furthermore, fleet parameters like the average fleet SOC, total driven distance or total energy demand are updated. These parameters serve for evaluation purposes.

Next, the central and most important part of the simulation, the Logistics Control Unit (LCU) is executed. The LCU coordinates the fleet and serves two main purposes:

1. Ensure compliance with the vehicles battery operating limits in terms of energy content
2. Allocate vehicles to containers

The remaining energy content of each vehicle is monitored in every time step of the simulation preventing any battery operating limit violation. Two different kinds of monitoring are mandatory. Firstly, vehicles currently not assigned to a mission have to be monitored. This is done by calculating the energy demand for the route from the current location of the vehicle to the charging position. If the remaining energy content gets below this energy demand, under consideration of a safety margin of 20 %, the vehicle is assigned to drive to the charging position. Secondly, it has to be ensured, that battery limits of all vehicles are not violated during the fulfilment of any mission. This is realized by the implementation of a security check in the allocation process. The total energy demand for the driving missions, loading and unloading procedures and the way back from the destination to the charging point is determined considering the aforementioned safety margin. If the value exceeds the remaining energy content of the vehicles battery, the vehicle is not considered for the allocation to this specific mission.

The second main task of the LCU is the allocation of vehicles to container transportation orders. The LCU creates two overviews: all available vehicles and all unassigned containers. In order to find out the best solution while matching containers with vehicles, a scoring system is developed to enable the evaluation of vehicle-container combinations. The following parameters are used for the evaluation of the existing combinations:

1. Energy demand
2. State of charge
3. Container waiting time

For each parameter, a matrix is created containing the respective values. In the case of the energy demand, each entry represents the amount of energy needed for the vehicle to drive to the pick-up location of the container and deliver it to the requested drop-off spot. To calculate the payload-dependent energy demand for a mission, a linear interpolation between the pre-simulated results based on the aforementioned discrete payload distribution is performed. Furthermore, the energy demand during the pick-up and drop-off procedure is considered. The format of the resulting matrix for the cumulated energy demand is described by the equation below, whereas n describes the amount of available vehicles and m the amount of unassigned containers.

$$E_{cum} = \begin{pmatrix} \Delta E_{11} & \cdots & \Delta E_{1n} \\ \vdots & \ddots & \vdots \\ \Delta E_{m1} & \cdots & \Delta E_{mn} \end{pmatrix} \tag{1}$$

The created matrix is normalized and each value is converted to a user-defined scale. In the example at hand, a scale of one to ten is chosen, whereas one is the worst and ten is the best score. In case of the energy demand, one is set for the highest demand and ten for the lowest. The vehicle with the lowest SOC will be scored with a ten, the highest SOC with one. This avoids, that all vehicles simultaneously discharge their batteries to a level, where, in a worst-case scenario, the whole fleet would have to drive to a charging station at the same time. Thereby the logistics system would come to an abrupt halt. The waiting time of a container is considered as measure for a quick delivery, which is a key performance indicator for a logistics system. Therefore, the score one is given for the shortest waiting time, ten for the longest. This consideration also prevents, that a container on a remote location is ignored by the system due to a remote pick-up or drop-off location, hence resulting bad energy score.

A weighting methodology is applied to reduce the complexity of the problem from three to two dimensions. The formula to calculate the absolute score for a vehicle-container combination is shown in the equation below, where w_{ij} is the absolute score and g_k the respective weighting factor for the respective value.

$$w_{ij} = g_1 * \Delta E_{ij,norm} + g_2 * SOC_{i,norm} + g_3 * t_{w,j,norm} \quad (2)$$

The set of parameters used for the weighting factors is pictured in the table below.

Table 2: Initial parameterization of the weighting factors

Weighting factor	Value
Energy demand	0.4
State of charge	0.3
Container waiting time	0.3

With the determined normalized, scored and weighted matrix, the three-dimensional problem is reduced to a two-dimensional problem. The maximum sum of entries has to be found, where no vehicle is assigned to two containers or vice versa, to solve the problem and to find the optimum solution. This problem description fits the description of the known assignment problem. A solution to this problem has been proposed by H. Kuhn [18] and was improved by J. Munkres [19]. An implementation of the so-called "Hungarian Method" is used in the LCU for solving the problem.

After the LCU module is complete, the CCU element is executed. The task of the CCU is to monitor and control the charging site in the logistics system. It ensures that the number of vehicles charging does not exceed the number of charging positions available. Furthermore it ensures, that the charging spot is handed over to the next vehicle in line when the charging processes completed. In the last step, the simulation time is updated and the time step is completed.

For the investigated use case, 2500 container transports per day with fully randomized distribution of pick-up and drop-off locations and a constant average container mass of 13 t are investigated. A logistics plan is generated for a duration 24 h based on these inputs.

3 Verification and Results

The results of the environmental simulation are verified with measured data from a battery electric terminal tractor gathered in a previous project. [3] The main goal of this verification is to ensure, that the road pattern of

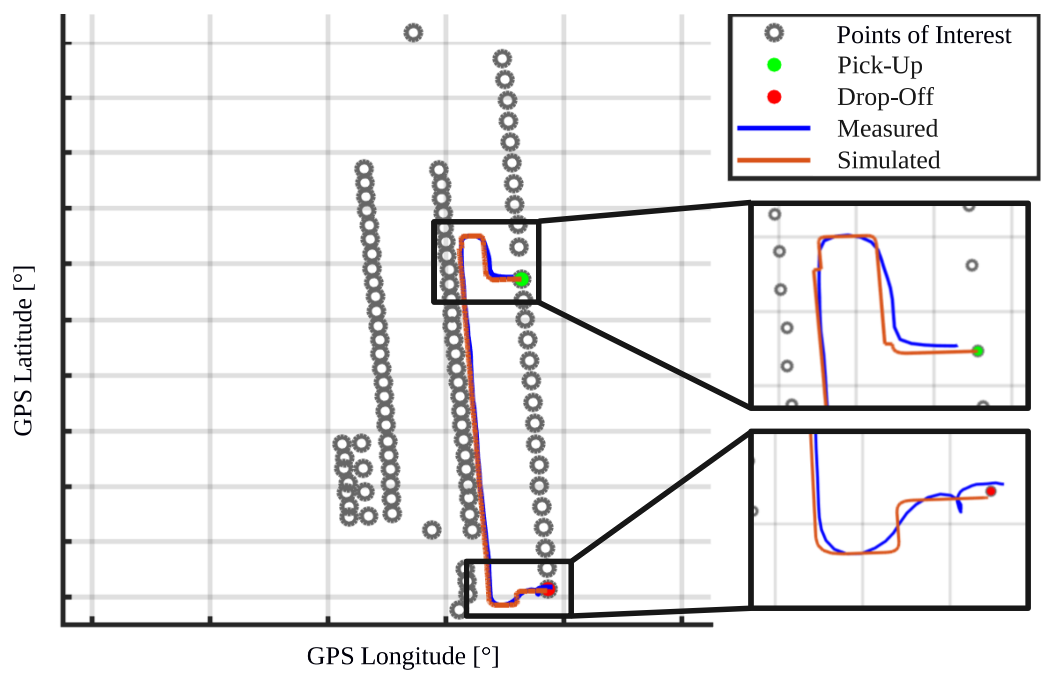

Figure 5: Route comparison between GPS traces of simulation and measurement

the port is correctly implemented in the simulation. For this reason, the measured GPS position of the vehicle is compared with the GPS position of the vehicle in the simulation, as shown in the following figure.

The route course comparison and further analysis is conducted by evaluating the available measured data. The dotted elements in the figure represent the POIs in the simulated road network. The graphs show the GPS trace of both the measured and the simulated vehicle. In this example, the same route, defined by pick-up and drop-off point, leads to comparable vehicle positions. No direct information regarding the payload is included in the measurement data. Therefore, the data is narrowed down to sections where no trailer is attached. This prevents false verification results concerning velocity profile and the energy demand of the vehicle. Furthermore, a route and position recognition is implemented to compare the measured data with the results of the environmental simulation. The created dataset is used to evaluate the simulation in terms of the driven distance per route, the time needed per route and the average velocity on each route. The results of this verification are shown in the table below.

Table 3: Results of the environmental simulation verification

	Error in time	Error in distance	Error in avg. velocity
Median	-11.89 %	0.37 %	12.43 %
25th Percentile	-28.37 %	-9.18 %	-5.21 %
75th Percentile	11.35 %	7.43 %	31.6 %
Mean	-9.91 %	1.64 %	11.76 %

The table shows the relative deviation between the simulated and measured values for all simulated routes. The simulation runs are evaluated statistically to identify both the quality and robustness of the simulation results. The relative errors vary by more than 30% for the majority of the simulation runs regarding time and velocity. This shows the necessity for further investigation regarding this topic. The evaluation of the driven distance shows better results. The median value as well as the mean error indicate a good fit of the simulation results compared to the measured data. In addition, the scatter band to cover the 50 % smallest relative errors of around 17 % is significantly smaller as for the other evaluated parameters. This correlates with the comparison of the GPS-courses in the above shown Figure 5. The overall course of the route is well met, though improvements can be done to the implementation of the driven curve radii.

The vehicle simulation is verified by an evaluation of the energy demand per route using the aforementioned narrowed down data with no trailer attached. The measured velocity profiles for the single routes serve as input for the vehicle simulation. The corresponding velocity profiles from the environmental simulation are not used here in order to focus on the results of the vehicle simulation and prevent influences from the above-described errors on the following model verification. The results of this verification are shown in the table below.

Table 3: Results of the vehicle simulation verification

	Error in energy demand
Median	0.27 %
25th Percentile	-6.70 %
75th Percentile	8.60 %
Mean	-2.23 %

The results of the median and the mean error suggest, that the overall energy demand is well fit by the model. Furthermore, the scatter band of around 15 % suggests, that a further investigation of the use case is necessary. Due to the lack of specific datasheets for the components used in the measured vehicle, scaled efficiency maps are being used for several components. Despite the possibility to make use of a dynamic auxiliary power consumption in the vehicle simulation, currently constant values are used. Reason for this is missing information about the exact setup and the behaviour of the auxiliary components of a terminal tractor as well as the unknown environmental conditions during the measurement. Both of the aforementioned aspects are seen as reasons for the scatter band of the simulation results.

The verification of the logistics simulation is divided into two parts. In the first step, the internal verification process during the simulation is described. In the following figure, the trace of the average fleet SOC and the SOC trace of each vehicle is shown. In this case, a fleet of 20 vehicles is investigated.

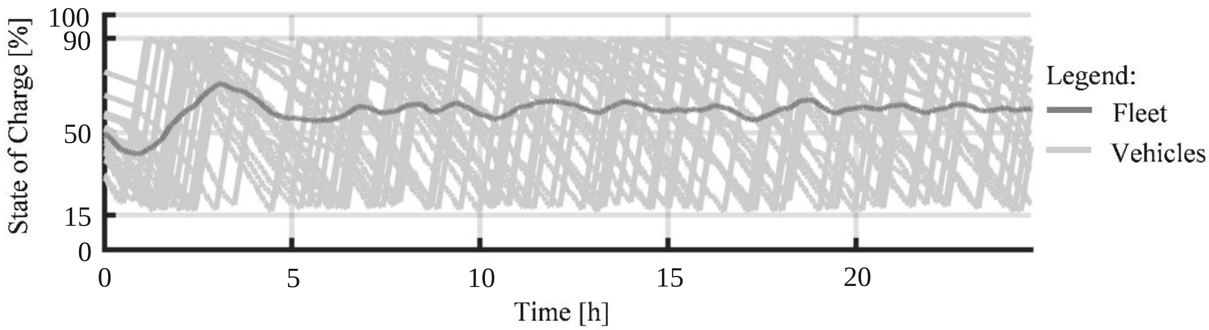

Figure 6: Fleet and vehicle SOC in the logistics simulation

The figure above shows, that the fleet management is capable of keeping all, in this case 20, vehicles within the predefined SOC range and none of the vehicles stops due to an empty battery. This demonstrates that the LCU as well as the CCU are working according to the set requirements. The initial SOC of each vehicle at the beginning of the simulation is chosen randomly around 50 %. During the first two hours of the simulation, the average fleet SOC drops below 50 % but stabilizes around 60 % thereafter, indicating a sufficient availability of charging infrastructure and charging events per vehicle.

The second part of the verification consists of a verification for the simulation approach proposed in chapter 2.3.1. Aspects to proof are the interpolation method to determine a mission's payload dependent energy demand and the difference in calculation methods and time step sizes of vehicle and logistics simulation. Furthermore, the simulation of the charging process in the logistics simulation is being evaluated. The compliance with the SOC-dependent power limits of the battery and the predefined DOD-limit concerning the energy content of the battery is verified. To do so, the complete cycle data for each vehicle consisting of a velocity, auxiliary power and payload profile is extracted from the logistics simulation results and fed back into the vehicle simulation. The verification results are displayed in the table below.

Table 3: Results of the logistics simulation verification

	Value
Mean error energy (discharge)	0.66 %
Mean error energy (charge)	0.55 %

The evaluation shows, that the error caused by this methodology in general is low and the methodology can thus be seen as validated.

The verified model is finally used for an exemplary investigation of the performance of different system configurations in the given use case. The results hereof are shown in the table below.

Table 3: Results of the logistics simulation

Configuration	I	II	III	IV
Number of vehicles	20	15	15	17
Battery energy content (DOD)	112.5 kWh	112.5 kWh	112.5 kWh	112.5 kWh
Number of charging points	10	10	10	10
Charging power (per charging point)	150 kW	200 kW	100 kW	150 kW
Total energy demand	10.41 MWh	9.65 MWh	9.36 MWh	8.59 MWh
Avg. charging power (grid)	459 kW	425 kW	306 kW	369 kW
Max. container waiting time	1 sec	19 min	32 min	2 min

The size of the fleet and the available charging power per charging slot are varied. The usable battery energy content and the amount of charging slots are kept constant. In the lower part of the table, the key performance indicators of the systems in terms of energetic performance and logistical capability are displayed. The logistical performance is measured based on the maximum container waiting time, defined by the duration from the appearance of a container to its assignment to a vehicle. As seen in the table, configuration I performs best regarding the waiting time. The maximum waiting time being at the lowest possible value suggests an overcapacity due. Configuration IV shows the second lowest value. The configurations II and III perform worse at high maximum waiting times revealing that these systems are operating near or above their logistical capability. The container waiting time distribution of configuration III is shown in the figure below.

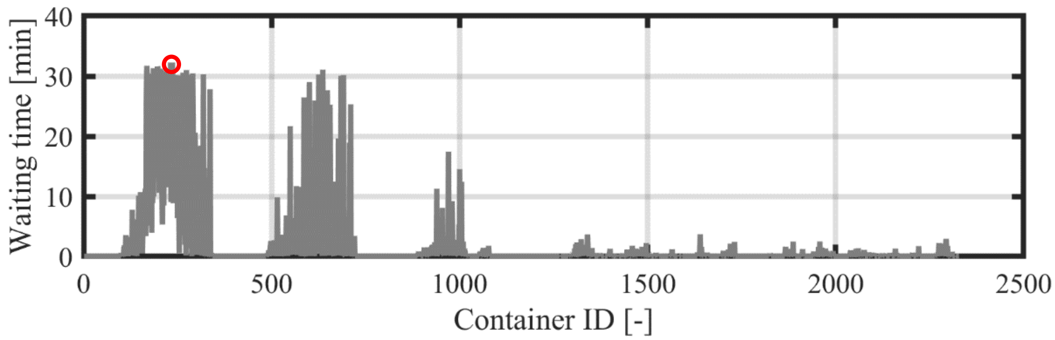

Figure 6: Container waiting of configuration III

The figure demonstrates the frequent occurrence of longer container waiting times over the course of the simulation around the singular maximum waiting time marked at Container ID 250. This further is an indication to an insufficient logistical capacity of this system.

It needs to be pointed out that configuration IV is the most energy efficient system of the ones presented, although neither its number of vehicles nor the charging power are the minimum or maximum values investigated. This suggests an optimal configuration can be found within the variation of configuration parameters. This configuration is able to provide the required logistical capacity while having minimal energy demand.

The simulation environment implemented therefor enables a holistic investigation of the heavily reciprocal influence of the fleet parameters onto each other. Furthermore, it marks the foundation for an optimization approach to enable the investigation of a logistics system in terms of economical as well as ecological aspects.

4 Summary and Outlook

Environmental protection regulations lead to increasing importance of electrification of commercial port vehicles. Due to the nowadays higher technology costs compared with conventional solutions, avoidance of over-dimensioning through tailor made competitive technology configurations can facilitate the transition to emission-free transport in this application. In the paper at hand, a development tool for the conception of electric vehicle fleets in logistics system is proposed and evaluated based on a reference scenario. By combined consideration of all three layers: environment, vehicle and infrastructure technology and logistical processes. Requirements regarding the vehicles battery energy content and mandatory charging infrastructure installation to keep the fleet operational are derived. Feasibility is verified by a similar container delivery time compared with the current conventional vehicle fleet operations in the scenario. A possible utilization of the method and results can be the procurement process of operators planning to shift their fleet to electric.

In the next step, the research results presented are applied in the national research project “ZETT – Zero Emission Terminal Tractor” funded by the German Federal Ministry for Traffic and Digital Infrastructure [20]. Based on the operation schedules of three national ports, vehicle fleet and infrastructure layouts are proposed for each custom use case. A prototype vehicle is configured according to the findings and tested in the field. The combined simulation environment is enhanced, to meet the technology requirements and configurations of the project.

Additionally it is extended with the functionality of a life cycle analysis as an additional economical layer. By this, the weighing e.g. between extended battery energy content or increased amount of charging infrastructure can be evaluated in more detail. Effects such as aging and expected lifetime are planned to be considered.

Moreover, the simulation environment can be used to verify vehicle operations online as shown in the paper. The simulations are already equipped with co-simulation interfaces to modify them during run time. Thereby, embedding of online optimization tools or implementation of dedicated third-party software regarding logistics management is prepared. One step further, vehicle operations can be optimized by adapted disposal of vehicles based on the logistics schedule. The basic charging strategy presented above can be enhanced to an online version, taking the current state of charge of the vehicles as well as the predictive operation schedule into account to increase the efficiency of the system. From an energetic point of view, this could be achieved through reduction of unladen trips, adjustment of charging power and duration or dedicated vehicles in a heterogeneous fleet with a spectrum of battery capacities. The aim is to reduce over-dimensioning further while keeping the logistics performance up. From an economical point of view, the total lifecycle costs may be reduced further by reducing the fleet size or battery wear. Progress in autonomous driving technology will enable applications in the operations of terminal tractors, which are nowadays restricted due to the mixed use with external tractors entering the port grounds and insufficient sensor maturity. Beneficial effects can already be seen for electric autonomous guided vehicles [21] in a similar application. These drafted applications for the combined simulation environment will be investigated in more detail in the future.

The presented algorithms will be part of the baseline for the project “BEE” (BEV goes eHighway), funded by the German Federal Ministry for Environment. Use of these will be to enable the in depth fleet and vehicle evaluation.

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