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An Agent-Based discrete event simulation of teleoperated driving in freight Transport: The fleet sizing problem

Bahman Madadi [a,d,*], Ali Nadi [b], Gonçalo Homem de Almeida Correia [b], Thierry Verduijn [c], Lóránt Tavasszy [b]

[a] École Nationale des Travaux Publics de l'État (ENTPE), 3 Rue Maurice Audin, 69120 Vaulx-en-Velin, France
[b] Delft University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands
[c] Rotterdam University of Applied Sciences, G.J. de Jonghweg 4, 3015 GG Rotterdam, The Netherlands
[d] Gustave Eiffel University, 25, avenue François Mitterrand, Cité des mobilités. 69675 Bron, France

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ABSTRACT

Teleoperated driving complements automated driving and acts as transitional technology towards full automation. An economic advantage of teleoperated driving in logistics operations lies in managing fleets with fewer teleoperators compared to vehicles with in-vehicle drivers. This alleviates growing truck driver shortage problems in the logistics industry and save costs. However, a trade-off exists between the teleoperator-to-vehicle (TO/V) ratio and the service level of teleoperation. This study designs a simulation framework to explore this trade-off generating multiple performance indicators as proxies for teleoperation service level. By applying the framework, we identify factors influencing the trade-off and optimal TO/V ratios under different scenarios. Our case study on road freight tours in the Netherlands reveals that for any operational settings, a TO/V ratio below one can manage all freight truck tours without delay, while one represents the current situation. The minimum TO/V ratio for zero-delay operations is never above 0.6, implying a minimum of 40% teleoperation labor cost saving. For operations where a small delay is allowed, TO/V ratios as low as 0.4 are shown to be feasible, which indicates potential savings of up to 60%. This confirms great promise for a positive business case for the teleoperated driving as a service.

Introduction

The automotive industry anticipates a fundamental transformation through the integration of connected and automated vehicle technologies, which promise to deliver enhanced road safety, optimized traffic flow, improved passenger comfort, and reduced environmental impact while facilitating innovative mobility solutions including autonomous taxi services, shared vehicle platforms, and coordinated freight convoy system (Milakis, Arem and Wee, 2017). While advances in vehicular hardware and communication infrastructure have made it possible to deploy these technologies in specific, well-defined scenarios—such as highway travel during favorable weather—substantial technical obstacles persist in achieving comprehensive automation across diverse driving environments and varying operational conditions. Tests of automated vehicles in the United States have revealed that current systems struggle to consistently and perfectly execute all dynamic driving tasks, especially in the intricate settings of urban areas (Favarò et al., 2018; Lv et al., 2018). Some studies have proposed solutions to remedy this issue by adjusting the infrastructure and whitelisting to utilize automated driving on selected roads (Madadi et al., 2021; Madadi et al., 2020) or via dedicated lanes for automated vehicles (Chen et al., 2016; Madadi et al., 2021b). However, these solutions can be costly.

Teleoperated driving (TOD) enables humans to operate vehicles from a distance during challenging scenarios, facilitating the transition to full automation (Boban et al., 2018; Neumeier et al., 2018). Any teleoperation system comprises three elements: the robot (vehicle), operator interface, and communications link (Winfield, 2000). Teleoperated vehicles integrate cameras, sensors (radar, lidar), and potentially onboard processors for environment monitoring and perception. The operator interface includes displays for sensor information and input devices for vehicle control. The communication link enables bidirectional information flow between vehicle sensors and operator commands. TOD system definitions, design, and architecture are detailed in (Gnatzig et al., 2013; Neumeier et al., 2018), with various simulation tools

* Corresponding author.
E-mail address: bahman.madadi@entpe.fr (B. Madadi).

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proposed and tested (Neumeier et al., 2019; Hofbauer et al., 2020).

When it comes to road freight transport, shortage of available drivers in the freight industry is becoming a major concern in Europe (Ji-Hyland and Allen, 2022) and the US (Schuster et al., 2023). By 2030, Europe and the US will need about 6.4 million truck drivers but are projected to have only 5.6 million available under current working conditions (Veryard et al., 2017). In the Netherlands and Belgium, relatively undesirable labor conditions due to long working hours and extended periods of time away from home has caused a reduction in the number of drivers despite the increasing demand (de Winter et al., 2024). TOD could eradicate the necessity for working away from home in challenging conditions by transforming drivers to teleoperators who can work regular hours at the office and aid in tackling the growing operator shortages in the logistics industry.

The main economic benefit of teleoperation for logistics operators is expected to be lower labor requirements, especially where labor shortage creates an economic barrier. Teleoperation enables logistic service providers to keep a fleet of vehicles operational with fewer teleoperators than vehicles. While research on freight teleoperation economics is scarce, studies in adjacent transport sectors provide relevant insights: teleoperated taxi fleet deployment could reduce required drivers by approximately 30% (D'Orey et al., 2016), operational performance modeling in (Goodall, 2020) demonstrates how teams of teleoperators can monitor large automated vehicle fleets upon request, cost-benefit analyses of the operation of highly automated buses (levels 4–5) with remote operator support reveal viable business models (Hjelt, 2021), and teleoperation could address critical first/last mile challenges in trucking, reducing logistics costs and environmental impacts (Boban et al., 2018; Boker et al., 2025).

However, the viability of teleoperation in freight transport depends critically on teleoperator-to-vehicle (TO/V) ratios. Lower TO/V ratios yield higher cost savings but may compromise service quality through operational delays. This creates a fundamental trade-off that raises the critical question: **what is the optimal TO/V ratio for freight operations that balances labor costs with service quality?**

Despite this importance, a significant gap exists in the literature: no simulation framework currently exists for freight teleoperation planning, and since teleoperation is not yet operational for large-scale real-world testing, simulation represents the only viable approach to address this question.

Therefore, this study aims to explore the trade-offs between teleoperation service level and labor cost in road freight transport by developing the first simulation framework for freight teleoperation planning. Using a case study of road freight tours in the Netherlands, we determine optimal TO/V ratios across different logistics operations for given service levels and identify factors impacting optimal fleet size and teleoperation labor costs under various deployment scenarios.

The contributions of this work will benefit multiple stakeholders: logistics operators through reduced labor costs and alleviated the labor shortage issue, policymakers through enhanced infrastructure planning insights, and technology developers through clearer operational system requirements. Additionally, we provide an open-source simulation tool to support future research and industry application.

The remaining of this manuscript is organized as follows. Section 2 includes a description of our methodology and data collection. Section 3 describes the experimental setup and the case studies. Section 4 presents the results of the case studies as well as the analysis of the results. Finally, the last section contains the concluding remarks.

Methodology

The main aim of this study is to define the optimal TO/V ratio for a given teleoperation service level in logistics operations. Therefore, we design a simulation tool that replicates the teleoperator allocation and queuing processes of a teleoperation center providing teleoperated driving as a service to logistics service providers. The teleoperated driving simulation requires road freight tours as input to represent the teleoperation demand. Therefore, a simulation framework that replicates individual firms' logistics decision-making taking place at the level of shipments is required. To accurately estimate the teleoperation demand, we resort to MASS-GT, a multi-agent simulation system for goods transport that simulates the logistics decision-making behind freight transportation demand (de Bok and Tavasszy, 2018). It also simulates a large variety of decision-makers and choices at the level of individual firms considering agent-specific costs and constraints. The MASS-GT simulation model has been used widely in many real-world applications (de Bok et al., 2021; de Bok et al., 2022; Lopane et al., 2021; Tapia et al., 2023). Our methodology seamlessly integrates the teleoperation simulation tool developed in this study with MASS-GT to generate accurate estimations of road freight tours, use the generated tours as demand for teleoperation within the teleoperation simulation, and provide indicators for system performance under various scenarios. As shown in Fig. 1, the teleoperation simulator requires trips and tours data, which are generated within the freight demand simulator by running the shipment module and the scheduling module, respectively.

Our methodology contributes to the development of MASS-GT by adding another building block to it that enables it to evaluate futuristic and innovative solutions such as teleoperated driving, yet when the tour data is available, the teleoperation simulation module can be used as a stand-alone simulation application as in the case study used in this article. Fig. 1 shows how our simulation tool integrates with MASS-GT. The heart of MASS-GT encompasses two levels of logistic decision-making: long-term tactical choices, which are simulated in the shipment module, and short-term tactical choices, which are simulated in the scheduling module. These two fundamental modules simulate freight transport demand at the shipment level. The output of this simulation is a set of scheduled tours that transport simulated shipments from their origins to their destinations.

A shipment is a specific consignment of goods moved from an origin to a destination by a firm. A firm is a business entity engaged in providing or organizing freight transport services. The shipment module of MASS-GT synthesizes a set of shipments that are transported in the study area. To create this set of shipments, an event-based simulation is used for the four logistic processes: 1) producer selection; 2) distribution channel choices; 3) shipment size and vehicle type choice; and 4) desired delivery time (Lopane et al., 2021). The scheduling module simulates the formation of tours, chooses the time for each tour based on the desired delivery times, and optimizes the vehicle type choices. A trip involves movement of a vehicle from an origin to a destination to carry one or more shipment(s) and a tour is a sequence of trips performed by a vehicle before returning to its base or depot. Time-of-day decisions are simulated both in the Shipment module, and the Scheduling module. In the shipment module, first, a choice for the desired delivery time for each shipment is determined. In the scheduling module, the desired delivery time is considered in the selection of shipments that are considered for consolidation, the delivery order, and the tour departure time. For further information about this procedure, we refer the readers to (de Bok et al., 2018; Thoen et al., 2020). The product after running the shipment and scheduling module is a set of trips shaped in the form of tours for each firm. These tour activities are inputs for the teleoperation simulator.

The teleoperation simulator begins by processing tour activity sequences that have been simulated by MASS-GT in the study area. To determine a representative sample of tours, we make an assumption about the market penetration of the teleoperation system and then select a set of tours at random. Since the main purpose of the simulation study is to explore the optimal TO/V ratios given a certain level of service for teleoperation, the following assumptions are made.

- The simulation focuses on the driving tasks performed by teleoperators.

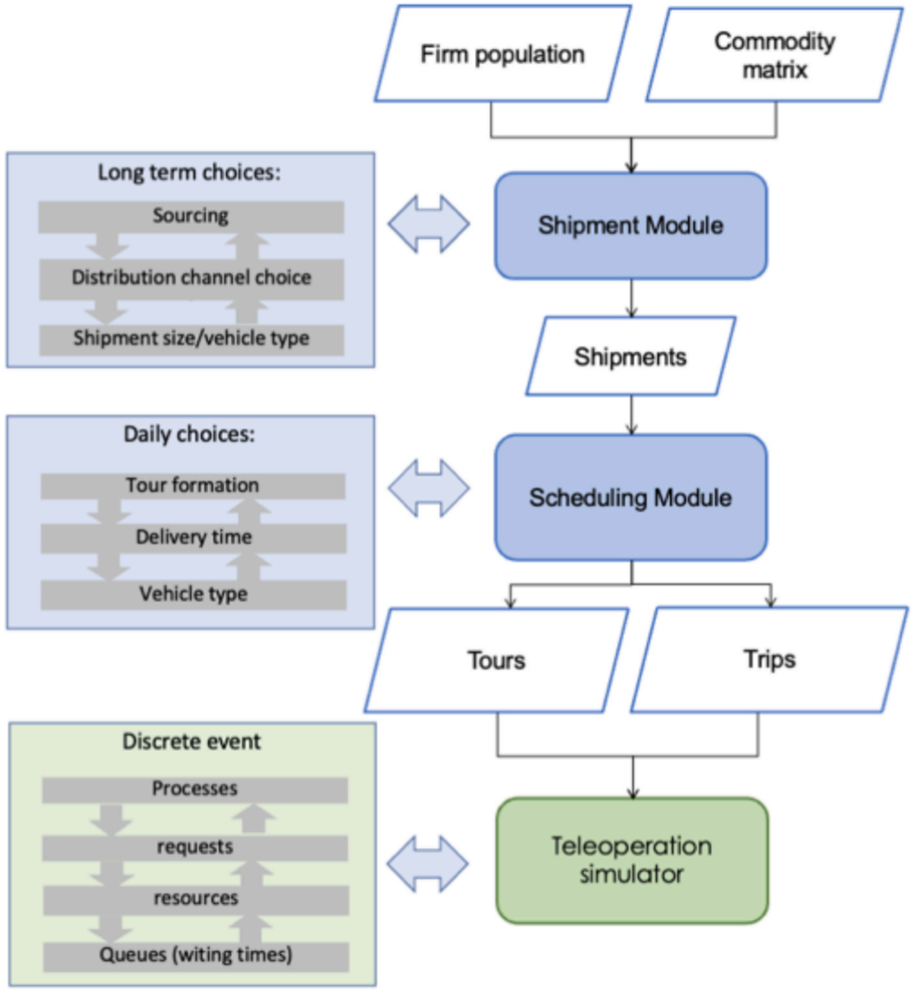


Fig. 1. Integration of MASS-GT with the teleoperation simulation.

- Driver responsibilities other than driving are not considered in the simulation.
- Company operations and activities will stay the same with teleoperation.

Given these assumptions, we propose a simulation procedure of teleoperation which is explained in the next subsection.

Simulation procedure

Our simulation is built upon Discrete Event Simulation (DES) techniques. DES is particularly appropriate for modeling teleoperated freight transport systems because: (1) the system naturally consists of discrete state changes triggered by specific events (e.g., teleoperator requests, teleoperator queue, tour completions); (2) it effectively captures the resource contention dynamics where a limited pool of teleoperators serves multiple vehicles; (3) it handles the stochastic nature of freight tour schedules and variable trip durations; and (4) there are standard mechanisms for collecting performance statistics essential for evaluating different TO/V ratios. The main components required for the discrete event simulation are the system, the entities (trucks), and the resources or servers (teleoperators). The system is the process or phenomenon being modeled by the simulation. In our case, the system is teleoperation of transporting goods from their origins to their destinations.

Each truck has a sequence of activities that defines its state. These activities have certain characteristics such as start, duration, and end, which are derived from MASS-GT tour data. During the simulation, the state of each truck can be updated as:

- Idle (buffer): when a truck is loading or unloading goods.
- In Queue: when there is no teleoperator available and the vehicle should wait in a queue.
- Takeover: when a teleoperator accepted the truck request and is taking over the control.
- Teleoperated: when the trip starts and the teleoperator is operating the vehicle.
- Signed off: when the vehicle has finished its tour.

Similarly, each teleoperator has a certain state variable which can be updated as follows:

- Idle: When a teleoperator is free and waiting for a request.
- Busy: when the teleoperator is operating a truck.
- Resting: when the teleoperator has reached its maximum allowed hours of teleoperation.
- Takeover: when a teleoperator is taking over the control of a truck.

The DES is also constituted by Events which are occurrences that trigger changes in the state of the entities and resources; the Time/clock that represents the passage of time through a series of discrete steps; and the Queues, which are places where entities can wait to be served by teleoperators. Since a limited number of teleoperators (i.e., resources) are available in each scenario, a queue might grow for teleoperators. This queue is modeled as a stochastic process based on the first in first out (FIFO) rule. Although the arrival process of this queueing model is determined based on the departure time of the trips (trucks request teleoperators at their departure times), this process is still stochastic. This is because the departure time of the tours in MASS-GT is based on the Monte-Carlo simulation of a discrete choice model that is calibrated based on real-world data of tour schedules (Thoen et al., 2020; Lopane et al., 2021). This queueing model is also a multi-server process as we can have m number of teleoperators in the system (see Fig. 2). The service rate and process time of each teleoperator depend on the duration of the trips that they are teleoperating and takeover times.

Finally, the last component of the DES is the Statistics which are used to record information about the system during and after each run. Examples of statistics include the number of entities in the system, the average waiting time for an entity, and the utilization of resources. These components work together (as shown in Fig. 3) to create a model of the system being simulated, which allows us to evaluate different scenarios and identify potential improvements.

After the initialization of the simulation parameters, the clock starts. For all trucks in the pool of vehicles, we select the first event in the activity list of the vehicle. If the vehicle state is Idle and the clock of the simulation is equal to the end of the Idle time, then the vehicle sends a takeover request to the teleoperator center. If all teleoperators are busy, then the truck should wait in the queue, and the queue processor adds to the length of the queue. Otherwise, a teleoperator will take over the vehicle and the status of the vehicle and teleoperator will be updated. Then, the truck's trip is simulated from the origin to the destination. When the trip ends, the teleoperator status will be updated to Resting if the teleoperator has been busy for a certain number of hours. If the tour has ended, then the vehicle status will be updated to signed off, otherwise, the next event in the vehicle activity list is triggered. Fig. 3 illustrates this simulation procedure in more detail.

Key performance indicators

In order to evaluate teleoperation scenarios, one needs to define key performance indicators (KPI).

Waiting time per vehicle is the first KPI we define is the average waiting time (wt) per vehicle where k represents each truck (K being the number of trucks), T^k represents the total number of trips in a tour that vehicle k must be driven. w_t^k is the time that truck k must wait in a queue before starting trip $t \in T^k$. Since the main aim of the study is to find the best balance between TO/V and service level, average wait time per vehicle is the most important KPI for this tradeoff since it is a common proxy for service level within the logistics sector. Additional KPIs provide more insight into the changes in the overall system performance.

$$wt_k = \frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{T} w_t^k \tag{1}$$

Waiting time per vehicle per queue indicates the duration of waiting each time a vehicle enters a queue. Therefore, it equals cumulative waiting duration for all vehicles divided by the total number of times that vehicles enter the queue (NQ).

$$wt_Q = \frac{1}{NQ}\sum_{k=1}^{K}\sum_{t=1}^{T} w_t^k \tag{2}$$

Vehicle utilization denoted as $Util_k$ is the amount of time each vehicle k is moving (TT_t^k is the travel time of trip t in the tour of vehicle k) divided by the simulation time ST.

$$Util_k = \frac{\sum_{t=1}^{T} TT_t^k}{ST} \forall k \in K \tag{3}$$

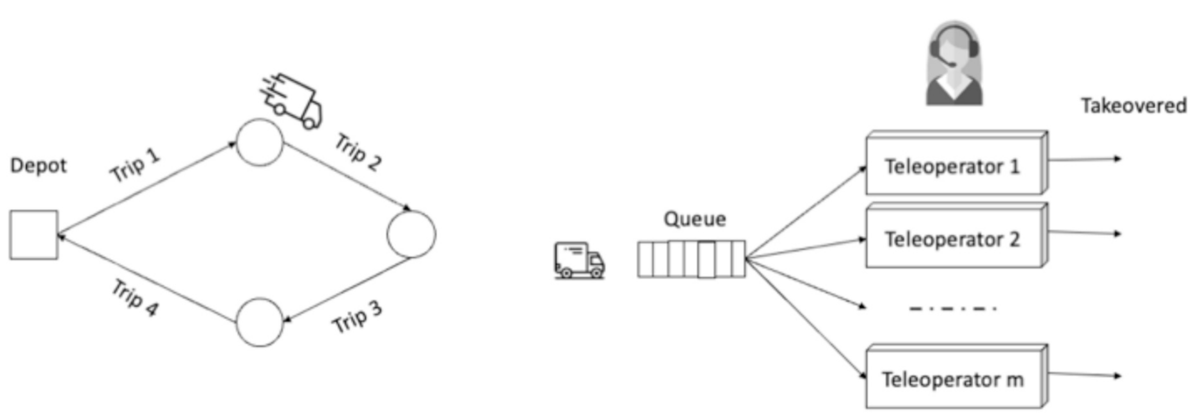
Teleoperator utilization represents the amount of time each teleoperator to in the set of teleoperators (TO) is busy driving a vehicle in trip t, including rest and takeover times, divided by the total simulation time and is defined as:

$$Util_{to} = \frac{\sum_{t=1}^{T} TT_t^{to}}{ST} \forall to \in TO \tag{4}$$

Makespan is another important KPI that allows us to compare scenarios and is defined as the total time required in the simulation to complete all tours and is calculated as below where su_t^k is the setup time (takeover time) of vehicle k in trip t.

$$Ms = \sum_{k \in K}\sum_{t \in T}\left(TT_t^k + su_t^k + w_t^k\right) \tag{5}$$

Tour Completion Rate (TCR) is the number of completed tours at



Trips	Idle start	Idle end	Queue start	Queue end	Takeover start	Takeover end	Trip start	Trip end
Trip1	8:00	8:15	8:15	8:15	8:15	8:17	8:17	9:35
Trip2	9:35	9:50	9:50	9:50	9:50	9:52	9:52	11:30
Trip3	11:30	11:45	11:45	11:48	11:48	11:50	11:50	12:25
Trip4	12:25	13:00	13:00	13:05	13:05	13:07	13:07	14:05

Fig. 2. Multi-server queue procedure and update of vehicle state characteristics.

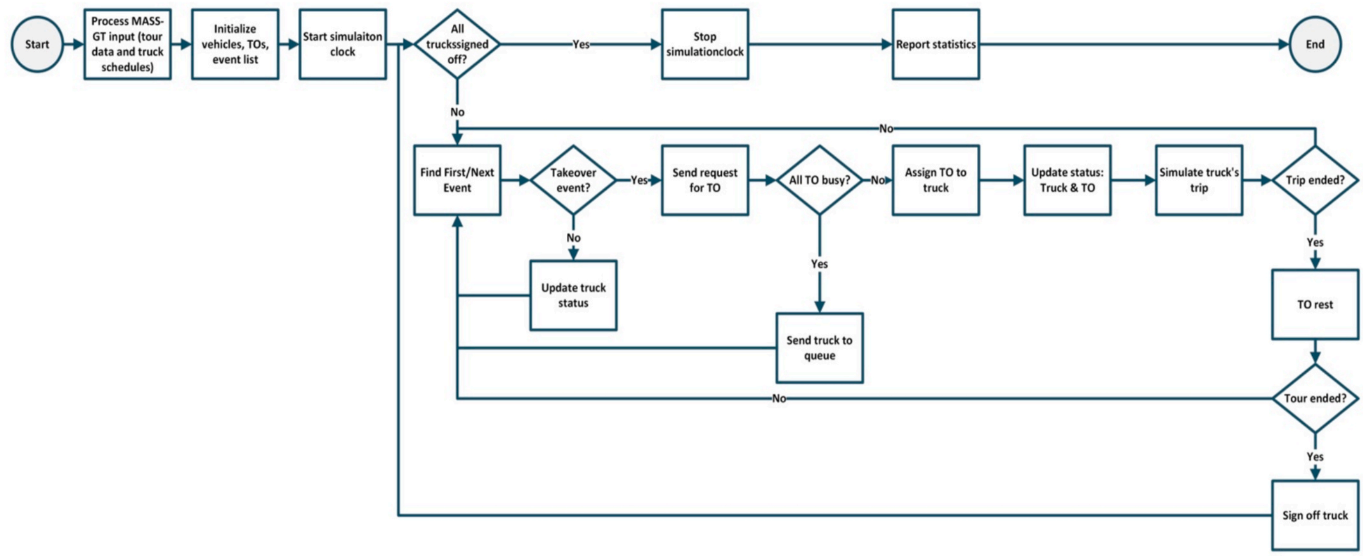


Fig. 3. Teleoperation simulation procedure.

the baseline makespan CT_{Ms_b} divided by the total complete tours at the scenario makespan CT_{Ms}. This KPI allows comparing the different settings of the teleoperation system with the baseline scenario.

$$TCR = \frac{CT_{Ms_b}}{CT_{Ms}} \tag{6}$$

Distance Completion Rate (DCR) is the total completed tour distance CTD_{Ms_b} at the baseline makespan divided by the total planned tour distance CTD_{Ms}. This measure provides a more accurate picture of the tour progress at baseline makespan. Consider the cases where tours are just remarkably close to being completed at the baseline makespan. Then the TCR cannot consider them as completed tours and hence shows a lower level of service for the system. Therefore, we use DCR in addition to TCR.

$$DCR = \frac{CTD_{Ms_b}}{CTD_{Ms}} \tag{7}$$

Delay rate is defined as the normalized difference between the total simulation duration of the scenario and the total duration of the baseline. Delay and TCR provide a clear comparison relative to the baseline in terms of how much delay is caused by queuing for teleoperators and the proportion of trips completed within the baseline makespan, respectively.

$$D = \frac{CT_{Ms} - CT_{Ms_b}}{CT_{Ms_b}} \tag{8}$$

To account for the uncertainty of the simulation results as well as the stochastic variations within runs, we report the average, standard deviation, minimum, median, and maximum of the KPIs derived from multiple replications of the simulation for each scenario. Mean and median values represent the expected predictions of each KPI, but deviations are of particular interest since in some cases, what defines the service level is the extreme value of a variable, for instance, maximum wait time per vehicle is useful for service providers planning to guarantee a wait time below a certain threshold for premium services.

Numerical experiments in the South Holland case study

To conduct a simulation experiment with a teleoperation simulator, the MassGT needs to be executed first, as shown in Fig. 1. The shipment module relies on both aggregated and disaggregated data from various sources. The Central Bureau of Statistics (CBS) of the Netherlands provides the primary source of data, using an XML interface to automatically extract microdata from the Transport Management Systems (TMS) of transport companies.

The data includes details on the vehicle, route, commodity type, weight, and loading and unloading locations, but not on the shippers and receivers of goods. To determine these locations, aggregate statistics from the Netherlands general business registration (ABR) data are used. Additionally, data on distribution centers (DC) and transshipment terminals (TT) are obtained from Rijkswaterstaat and contain information on their addresses, sizes, and sectors. The CBS trip diaries are enriched with this additional location information (Mohammed et al., 2023). These data provide MASS-GT with a firm population. Finally, the regional commodity flow data are derived from the Dutch strategic freight model "BasGoed" (de Jong et al., 2011). In the next section, descriptive statistics of the input and output of the MASS-GT simulator are provided in the study area. These data provide MASS-GT with inputs as well as ground truth for the calibration of the choice models. We refer readers to (de Bok and Tavasszy, 2018; de Bok et al., 2018) for further information about MASS-GT choice models and their calibration.

Descriptive statistics of the data

The study area of the current research is the province of South Holland and all freight transportation that takes place within, to, and from this study area. The simulation and its underlying behavioral models are empirically calibrated and validated based on large observed real-world logistics data. This data is available from an automated data collection of truck trip diaries among a sample of Dutch truck owners that is being collected by the CBS (de Bok and Tavasszy, 2018; de Bok et al., 2018; de Bok, Tavasszy, and Sebastiaan Thoen, 2022; Mohammed et al., 2023). The data includes information on the vehicles' characteristics, e.g., vehicle types and capacity, tours (loading and unloading locations and time), and shipment information within these tours, e.g., commodity type and size.

The firm population is generated and scattered across the Netherlands. Based on the activity type of firms and their density, the zones can be classified into Production or Consumption zones, Multimodal terminal zones, and zones with logistic activities like Distribution centers (see Fig. 4).

After running MASS-GT, the total number of tours simulated for an average day is just above 124,000 tours with more than 450,000 trips. For each simulation scenario, we filter all tours to select the ones that fall

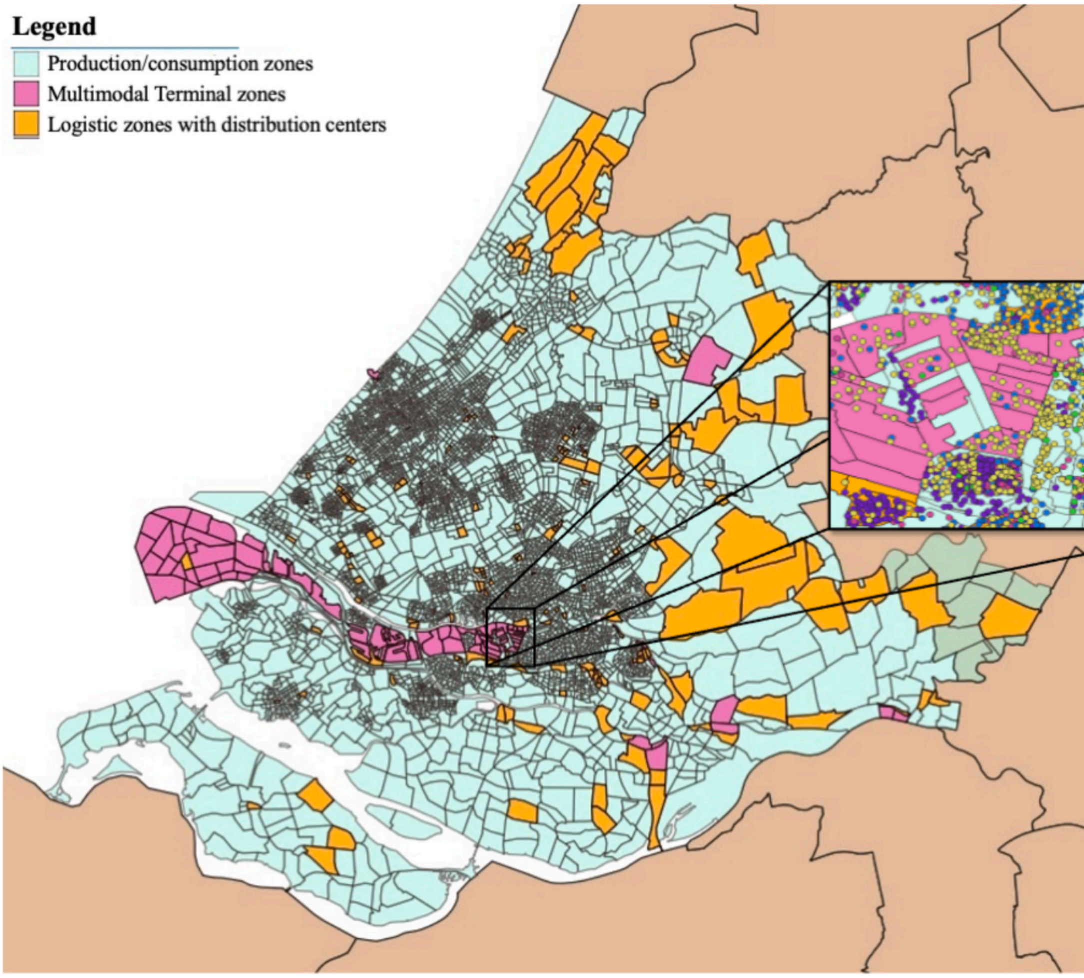


Fig. 4. Study area with the population density of logistic activities.

within the simulation time window according to the corresponding scenario (simulation start time and duration are scenario parameters). For each simulation replica within each scenario, we select 1% of the tours to be controlled by teleoperation (see Fig. 5).

Table 1 shows a descriptive summary of a sample of eligible tours for the base case scenario. These simulated tours are validated using the CBS XML data. We refer readers to (Thoen et al., 2020) for empirical evidence on the validity of the MASS-GT freight tour simulation.

Experimental setup

To evaluate the efficiency of teleoperation and potentially reduce the number of required human resources, we have designed various scenarios for this study. The TO/V ratio is the primary parameter in

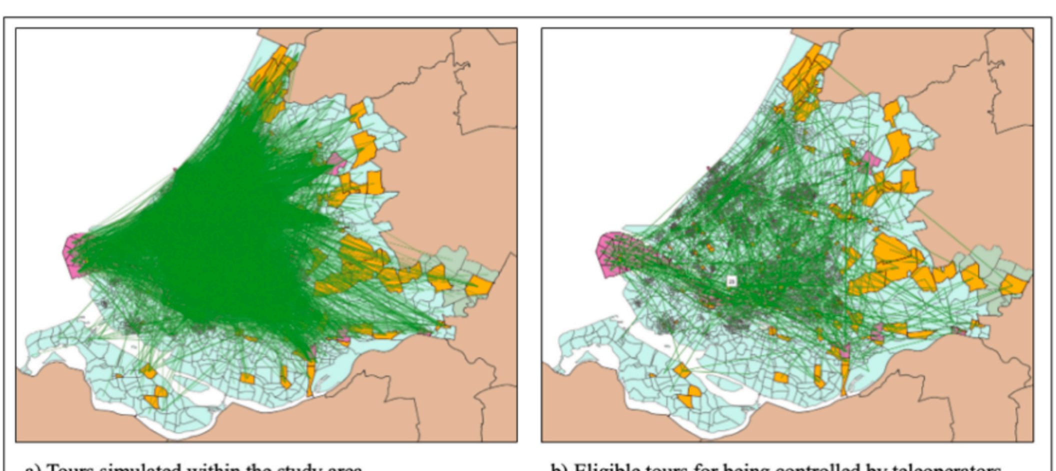


Fig. 5. Simulated tours in the study area and the eligible tours for teleoperation.

Table 1
General Descriptive Statistics.

Indicators	Values
Number of tours	454,170
The average number of trips per tour	4
Total number of tours	124,436
The average tour duration (hours)	7.37
The average trip duration per tour (hours)	3.71
Number of teleoperated tours	1244
Number of teleoperated trips	5326

defining these scenarios. Although lower ratios are more cost-effective, they may result in longer waiting times for vehicles and lower levels of service due to queuing for teleoperators. To strike a balance between teleoperator costs and service level, we used a grid of TO/V ratios ranging from 0.3 to 1. TO/V = 1 represents current practice (one driver per truck) and provides a human-driven baseline for comparisons. In our initial interviews with experts, we found that a short setup (takeover) time for teleoperators was necessary for safety reasons and to allow for situational awareness before driving. Therefore, we studied scenarios with one-, two- and three-minute setup times and included scenarios without this setup time for comparison purposes. One of the significant factors in the economic feasibility of teleoperated driving is the number of teleoperators required for a fleet of vehicles. Although reducing the number of teleoperators can decrease labor costs and improve utilization, it can also create inefficiencies in logistics facilities due to longer waiting times for trucks and occupying docks unnecessarily. The level of service of teleoperated fleet operations can be determined by the percentage of trips in which the waiting time of teleoperated trucks does not exceed the agreed maximum waiting time. However, this maximum threshold depends on the policies and level of resiliency of the freight transport system and needs further studies. We, therefore, use the waiting time itself as the proxy for the level of service of the teleoperation. Table 2 summarizes the parameters and variables in the simulation scenarios.

In this futuristic experiment, we assume that the market penetration of teleoperation will not exceed 1%. This is due to the requirement of advanced communication technologies that must be installed on the vehicles, which may not yet be affordable in the market, especially for small sectors. The willingness of the transportation industries to enhance their fleets with such technologies is still a topic for research and is beyond the scope of this study.

We have defined three different simulation start times which can be practically interpreted as the time that the teleoperation center starts its operation. Accordingly, two possible working shifts, namely 9 and 24 h, are considered for the design of the scenarios. Like truck drivers, teleoperators cannot control a vehicle continuously for safety reasons. Looking at monitors for a long time is also not healthy for teleoperators. Since there are no available experiments to quantify this threshold, we defined the same maximum allowable teleoperation hours (4.5 h) for the operators EUR-Lex-02006R0561 (2020). After this amount of teleoperation hours, the teleoperators must rest for 45 min. Teleoperators are also allowed to break down the rest into 10 min of short rest after each teleoperation. To the test he robustness of the results, we experiment with alternative rest times in the sensitivity analysis as well.

Verification and validation

In this section, we demonstrate the validity of our model using the three validation approaches outlined in (Sargent, 2013): conceptual model validation, operational validity, and data validation.

For conceptual model validation, we conducted extensive consultations with multiple logistics service providers operating in the Netherlands and Belgium through a series of meetings within the framework of the 5G-Blueprint project (EU Horizon project). The model's initial assumptions and operating procedures were thoroughly discussed during these sessions and subsequently documented in a technical report (Verduijn et al., 2021).

To establish operational validity, we executed the simulation model using real input data from three logistics service providers, representing the complete trucking operations of three medium-sized fleets. The simulation results were systematically compared with actual company statistics, demonstrating overall average deviations below 5% in mean, median, and standard deviations for driver status metrics (e.g., driving, resting) and utilization rates per company (Verduijn et al., 2021). While the proprietary company operational data cannot be disclosed, the statistical analysis results are fully documented and reported in (Verduijn et al., 2021). Moreover, we have executed the human-driven baseline scenario on a small sample of the open data without the stochastic trip elements and observed that the simulation generates the exact trip and tour start, duration and end times as the input as expected. This can be verified independently by other researchers and professionals using the code and the data provided as well.

For data validation, transparency, and reproducibility, this study employs the MASS-GT freight tour data described above, whose validity has been extensively tested and documented in (Thoen et al., 2020). Furthermore, we ensure independent community verification through the provision of open data and open-source code in our GitHub repository (link provided in the data availability section), enabling the community to validate and reproduce our findings independently.

As for the number of replications, we use five replications following the common practice in simulation studies as a pragmatic balance between computational efficiency and robustness (Law, 2017). In our case study, given five replications, the mean values are stable, and the variances are low as shown in the results. To formally confirm this stability, we report a statistical stability analysis given five replications in section 4.3, and a sensitivity analysis with higher replications in section 4.4.

Results and Discussion

In this section, we present the results of our simulation study. As can be seen in Table 2, a combination of all the settings allowed us to experiment with 360 scenarios through which we could examine teleoperation under extreme and non-extreme system conditions. In this section, we summarize the most notable findings from these experiments. We begin with an extreme scenario in which the vehicle-to-teleoperator ratio is the lowest (0.3), the working shift of teleoperators is 9 h, and the takeover time is 3 min. Next, we compare this scenario with the human-driven baseline (normal truck operation: TO/V = 1) for face validity. Then we explore the impact of various TO/V ratios and discuss a potentially optimal setting. Furthermore, we

Table 2
Scenario Variables And Parameters.

Scenario variable	Values	Description
Simulation start time	0:00 – 05:00 – 8:00	This defines the different settings for the start time of teleoperation within a day.
Simulation duration	9 h – 24 h	This defines the working shift of teleoperation within a day.
Ratio of teleoperators/ Vehicle	0.3–1	This allows us to investigate the level of service for different operator-to-vehicle ratio
Take over time	0, 1,2, 3 (minutes)	The time each teleoperator require to take over a vehicle
Parameter	**Value**	**Description**
Number of replications	5	The number of simulations run for each scenario
Market penetration	0.01 (1%)	The percentage of transport sectors that are eligible for teleoperation
Maximum allowable teleoperation	4.5 h	For safety and health-care reasons, each teleoperator is only allowed to control a vehicle for a maximum amount of 4.5 h.
Rest time	Short: 10 min Long: 45 min	Rest time for teleoperator after a teleoperation task.

examine the impact of different working shifts and simulation start times on the optimal scenario. Finally, we apply a cost-benefit analysis to estimate the financial performance of the teleoperation for the carrier.

Extreme teleoperation scenarios

In this scenario, the TO/V ratio is minimum, meaning that the number of teleoperators available in this system is only 30% of the number of vehicles. In this scenario, the takeover time is maximum since there is a lot of pressure on teleoperators, and hence higher time is needed for them to take over a truck. The working shift is 9 h meaning that the teleoperation center can only give service to vehicles for 9 h and the teleoperators start their work at 5:00 AM. This start time is aligned with the time that carriers often start their activities, and the duration will support the morning peak in teleoperator demand. We mark the end of the working time based on the human-driven baseline, which corresponds to the baseline makespan, by a vertical line to show the system state at this time but we continue the simulation until the completion of all tours in order to calculate delays and tour complication times under each scenario. The baseline makespan, which corresponds to the human-driven baseline, is indicated in figures 6 and 7.

Fig. 6 provides a comprehensive summary of the simulation scenario, depicting the number of vehicles engaged in different activities over the simulation timeline, along with the fleet size, the number of teleoperators who are either busy or idle at various points in time, the total number of available teleoperators, and the size of the teleoperator queue at each time interval. The figure offers a clear visualization of the key performance indicators and highlights the operational aspects of the system at various stages of the simulation.

The data shows that the queue size increases due to the limited number of available teleoperators. Additionally, the teleoperation scenario requires a longer duration to complete all tours compared to the baseline makespan. In other words, the distance between the vertical black line illustrated in Fig. 6 and the end of the simulation indicates the delay that teleoperation would pose to the system in a given scenario. This delay is attributed to the extended waiting time and takeover time, which teleoperation introduces to the system. Notably, a lower TO/V ratio would lead to longer waiting times, thus rendering the logistics system inefficient despite the reduction in teleoperator count. Hence, it is evident that the benefits of an exceptionally low TO/V ratio come at the cost of reduced efficiency and increased waiting times.

Table 3 shows the summary statistics of the key performance indicators for this simulated scenario over 5 replicas. Despite the desirably high teleoperator utilization rate of 72%, vehicle utilization is only 14%. Therefore, this scenario has the lowest level of service (indicated by the high waiting times in queues) as there are very few resources (teleoperators) to be assigned to each vehicle, and hence trucks must wait, on average, as long as 84.7 min in the queue for teleoperators. As we can see from Table 3, the freight transport system in this scenario will meet on average 86% delays in its operation, which imposes excessive costs on the system.

To represent the two ends of the spectrum in terms of the trade-offs between teleoperation labor cost and the level of service, we consider another extreme case where the TO/V ratio is equal to 1 and the takeover time is 0. The only difference between this scenario and common freight transportation is that each truck has one teleoperator instead of one truck driver. This scenario will not be beneficial for the business model of teleoperation since the objective of resolving the lack of truck drivers is not met. However, studying this scenario can provide face validity for the model and establish a baseline for evaluating the relative efficiency of other teleoperation scenarios.

In this scenario, the opposite phenomenon happens as compared to the previous extreme scenario (see Fig. 7). Since one operator is available for each truck, the queue length will always be zero. However, this comes at the cost of a low teleoperator utilization rate, thereby having many idle teleoperators at any point in time, which means higher labor costs. Moreover, as shown in Fig. 7, the number of busy teleoperators in this case never gets close to the number of available teleoperators (i.e., the instantaneous utilization rate of teleoperators never reaches 100%). This means a higher level of service (indicated by lower queue times) which comes at the price of higher labor costs due to a large number of teleoperators that are idling in the system.

By examining these two extreme scenarios on opposite ends of the experimental spectrum, we can conclude that there exists a trade-off

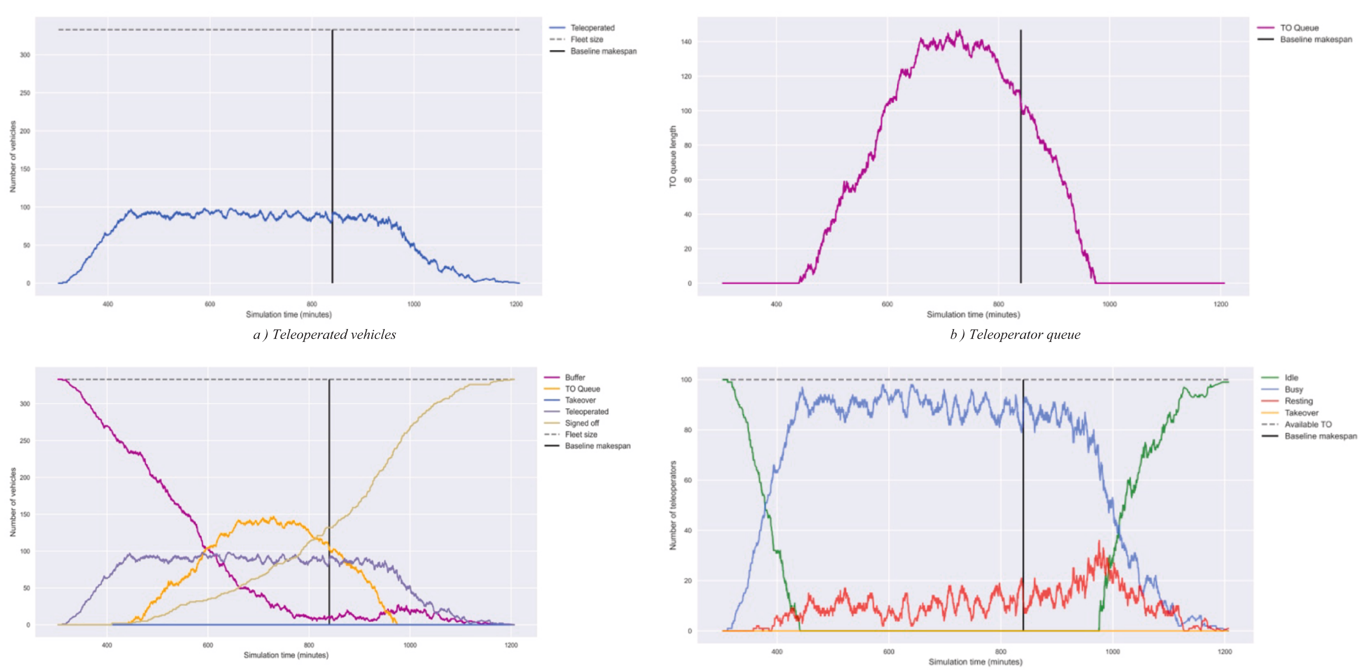
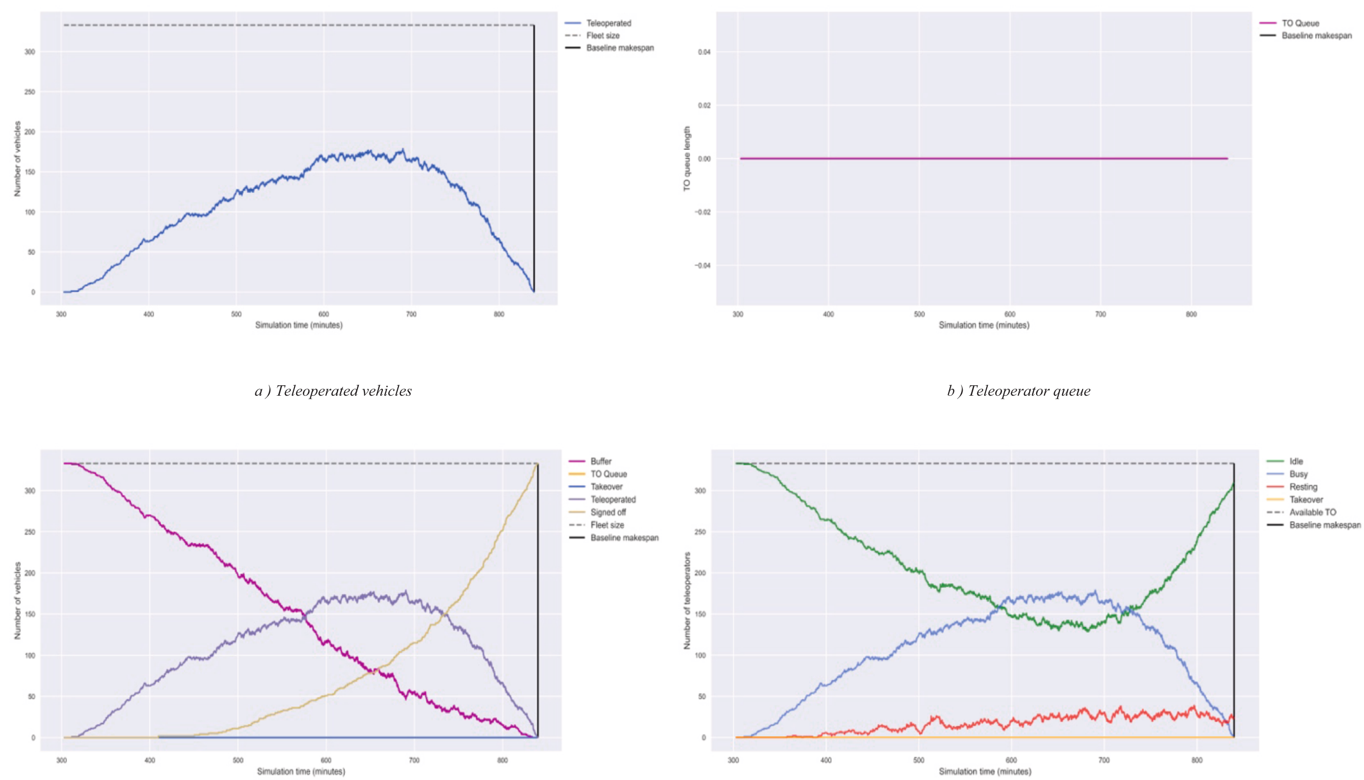


Fig. 6. Summary of teleoperation simulation for the TO/V ratio of 0.3. The black vertical line represents the baseline makespan corresponding to the human-driven baseline.

Table 3
Summary Of Key Performance Indicators For The Simulated Scenario With TO/V Ratio Of 0.3.

	mean	std	min	25%	50%	75%	max
AVG vehicle utilization ($Util_k$)	0.144	0.0055	0.14	0.14	0.14	0.15	0.15
AVG TO utilization ($Util_{to}$)	0.724	0.0055	0.72	0.72	0.72	0.73	0.73
AVG waiting time per vehicle (wt_k) (minutes)	142.292	8.8283	132.06	134.39	143.85	149.03	152.13
AVG waiting time per queue (wt_Q) (minutes)	84.724	3.8742	80.84	81.89	83.34	87.73	89.82
MAX waiting time per vehicle in queue (minutes)	139.54	7.2045	133.68	136.67	137.28	137.98	152.09
AVG queue length (# of vehicles)	38.716	1.9177	36.27	37.37	39.26	39.52	41.16
Max queue length (# of vehicles)	146.8	5.9749	137	146	148	151	152
AVG delay (D) (minutes)	0.8607	0.0366	0.8109	0.8421	0.8608	0.886	0.904



a) Teleoperated vehicles *b) Teleoperator queue*

c) Vehicle states *d) Teleoperator states*

Fig. 7. Summary of simulation for the TO/V = 1.0 (human-driven baseline).

between the cost of labor for teleoperators and the level of service provided. There is likely an ideal TO/V ratio that offers the optimal balance for this trade-off. In the following subsection, we will delve deeper into this topic to explore the potential trade-off.

Optimal TO/V ratio

In this section, we utilize different KPIs to discuss several factors that could impact the ideal ratio of teleoperators to vehicles. To this end, we explore the changes in the value of KPIs over different ranges of the TO/V ratio. These KPIs are tour completion, distance completion, delay rates, and average queue duration.

As evidenced by Fig. 8, with a TO/V ratio equal to 0.6 and starting time 0:00, all tours are completed, the average distance completion rate is 1 and the queue duration and delay in the system is almost zero. This means with only 60% of current human resources we can drive trucks without any loss. It clearly shows the potential gain of teleoperation in increasing the efficiency of the system. We could quantify the gain from this efficiency as follows:

$$GainRatio = \frac{N_{base} - N_{To}}{N_{base}} \times 100 \tag{9}$$

where N_{base} is the number of drivers in the base scenario (without teleoperation) and N_{To} is the number of teleoperators in the teleoperation scenario. Using Equation (10), we could for the scenario with a TO/V ratio equal to 0.6, we could conclude that the teleoperation system is 40% more efficient in terms of labor cost.

We should note that the loss in the system increases exponentially when we reduce the TO/V ratio to less than 0.6. However, with a TO/V ratio equal to 0.5, more than 90% of tours are completed, 95% of tour distances are driven, and the delay in the system ranges between 5% and 10% depending on the magnitude of the takeover time (see Fig. 8). In this scenario, trucks have a waiting time of no more than 4 to 10 min on average. These waiting times and delays pose operational costs to the system which can, to some extent, be compensated by the labor cost savings. To quantify the gain of the system in such cases, we require a more complex cost structure associated with a certain level of service of the teleoperation which can be calculated as the ratio of the difference between the current cost of transport minus the cost of running the

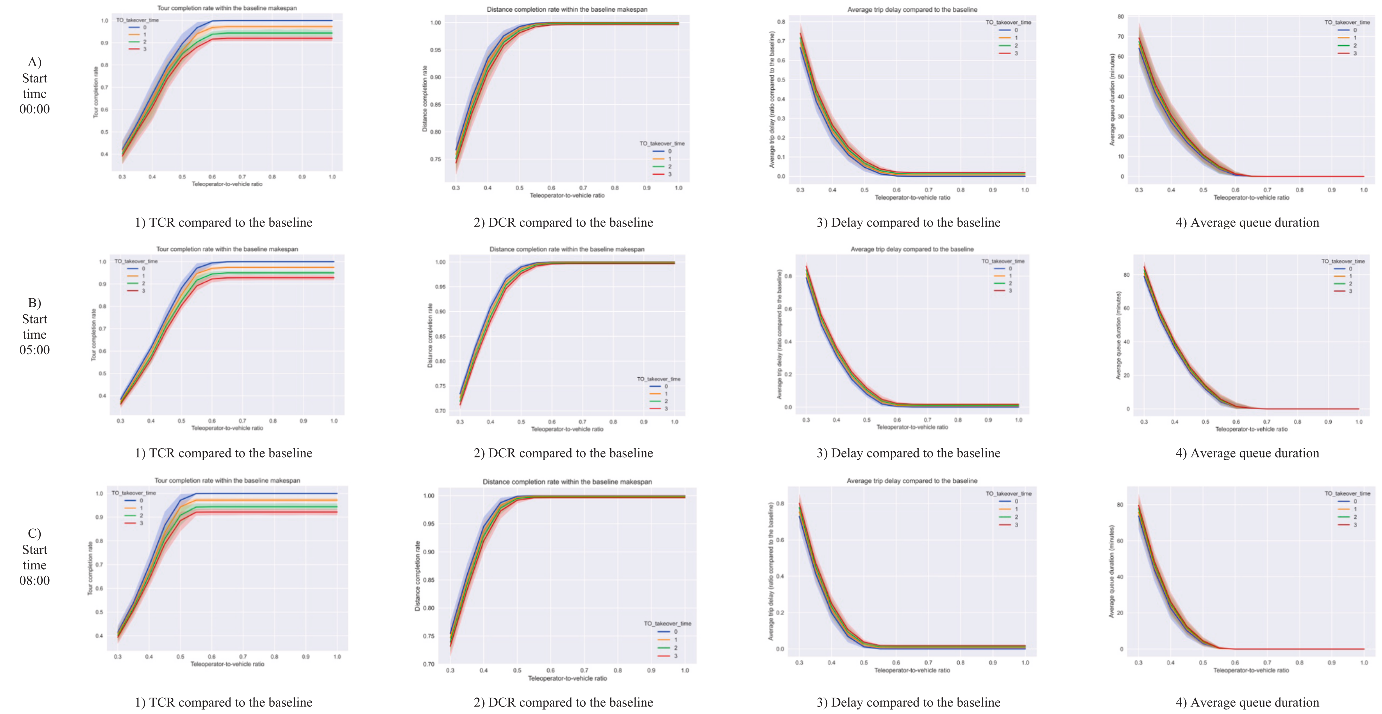


Fig. 8. KPIs versus TO/V ratio for different start time scenarios with 9 h of working shift.

transport with the teleoperation.

$$GainRatio = \frac{N_{base} \times MS_{base} \times w_{base} - N_{To} \times MS_{To} \times w_{To}}{N_{base} \times MS_{base} \times w_{base}} \tag{10}$$

where MS_{base} is the simulation duration (makespan, see Equation (5) in the base scenario, MS_{To} is the simulation duration or makespan in the teleoperation scenario, and w_{base} and w_{To} is the drivers' and teleoperators' hourly wage, respectively. Assuming equal hourly wages for the truck drivers and teleoperators, equation (8) can be simplified as follows:

$$GainRatio = \frac{N_{base} \times MS_{base} - N_{To} \times MS_{To}}{N_{base} \times MS_{base}} \times 100 \tag{11}$$

Using the simulation model presented in this study and based on the results of the multiple simulation scenarios, the optimal TO/V ratio can be specified for any given level of service defined by any KPI (e.g., max queue duration or average delay). For instance, considering the average queue duration as a service level indicator, the lowest number for the TO/V ratio (the most economical option) can be specified for any desired average queue duration. The results depicted in Fig. 8 show that to ensure an average wait time below, for example, 20 min, a TO/V ratio of 0.5 will suffice (see Fig. 8).

In this scenario, the makespan is 560.1859 and 598.1721 min for the baseline and teleoperation scenarios respectively. The number of truck drivers in the baseline is 250 and the number of teleoperators in the teleoperation scenario is 125 (TO/V = 0.5). Using Equation (11), the gain of the system is 47% which exceeds the gain in the scenario with the 0.6 TO/V ratio (no delay scenario). This means that the lower labor costs associated with the lower TO/V can compensate for the higher costs associated with the higher makespan (delay).

Fig. 8 also shows that a lower TO/V ratio can be achieved without any loss if the teleoperation starts at 8:00 as compared to the start time 0:00 or 5:00. By tolerating only 10 to 15 min of average queue time, one could complete more than 95% of the tour distances with a TO/V ratio of 0.45 within the baseline makespan. The average gain of this scenario is 49%. The reason we can achieve higher gain with a lower TO/V ratio in this scenario is that tours starting after 8 include more trips (legs) as compared to the tours starting earlier in the morning. Therefore, the buffer time between trips allows teleoperators to drive more vehicles. It should be noted that the higher takeover time can slightly reduce the gain. However, this loss is relatively very low and hence negligible. We also would like to bring to the attention that these gains are potentially achievable with only 1% teleoperation market penetration rate. For a higher teleoperation rate, we could expect much larger gains.

We also explored the performance of the teleoperation for the 24-hour working shift. Fig. 9 shows the KPIs for different start time scenarios with 24-hour working shifts of teleoperation. The most salient finding from this figure is that with the larger time span that the teleoperation system is active, a lower number of teleoperators is needed to drive all vehicles. Among all scenarios, the best TO/V ratio is 0.3 where the start time is 0:00 and the working hours of the teleoperation center is 24 h. In this scenario, we have 250 teleoperators that drive 800 vehicles. It is evident that trucks must wait between 4 and 12 min on average to be assigned to a teleoperator which leads to a makespan of 1530.855 (the baseline makespan is 1472.246 min). The total gain of this system is 67% for the simulated day (using Equation (11). It should be noted that higher gains in 24-hour scenarios are partially due to the wider spread of peak times within the 24-hour working shift, more idle times within the system that affect all averages, and the higher number of teleoperators in the system due to having a higher number of tours in 24-hour work shifts.

It should be mentioned that the gain calculation in this study is limited to labor costs only. One could argue that the longer makespan associated with a lower TO/V ratio may pose other costs like late delivery to the operators. Please note that a longer makespan does not necessarily mean late delivery. This mainly could mean that the same amount of delivery will be scheduled for a longer time window. We, therefore, may require different tour planning within the concept of teleoperation. However, we believe that unreliability in the teleoperated freight transport, that are attributed to queues and takeover times, can pose extra costs to the operators. In (de Jong et al., 2014), authors calculated the value of reliability (VOR = 15 Euros/hour for 2–40 tone trucks) and the value of time (38 Euro/hour for 2–40 tone trucks) for freight transport in the Netherlands using collected stated-preferences

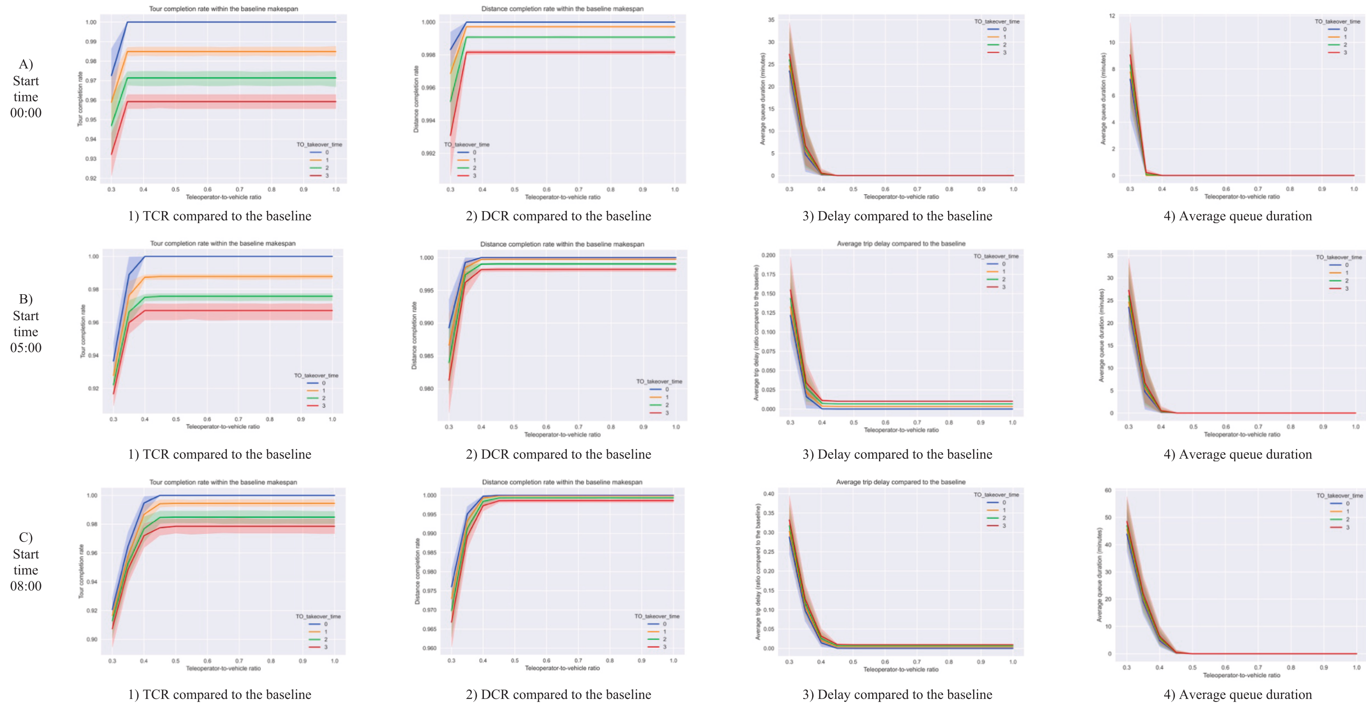


Fig. 9. KPIs versus TO/V ratio for different start time scenarios with 24 h of working shift.

data. In their research, the value of time (VOT) is associated with the expenses involved in offering transport services. If the duration of transportation decreases, it would free up vehicles and personnel for additional transports, leading to savings in vehicle and labor costs. The findings from the Netherlands and other countries suggest that the VOT linked to transport services aligns reasonably well with the hourly cost of vehicles and labor, particularly in the context of road transport (De Jong, 2007). Calculating the vehicle costs and reliability of transport in the teleoperation is beyond the scope of this research and hence ignored in favor of the teleoperation under a certain level of service thresholds that imposes delays. However, it is important to note that the absence of these calculations does not undermine the feasibility of teleoperation with a TO/V ratio of less than 1 and zero delays.

Moreover, in some cases, trucks waiting in queues may incur parking fees. Due to a lack of empirical data, these costs are challenging to measure in the study. Nevertheless, an interesting possibility could be the autonomous connection of trucks to nearby charging stations while waiting for a teleoperator in a queue. However, implementing such a scenario would necessitate a new planning and scheduling framework for teleoperation, which is beyond the scope of this study.

Statistical stability analysis

To ensure the statistical reliability of the simulation results given the stochastic nature of tour arrivals and service times, we performed a systematic analysis of the model stability relative to the number of replications. We utilized ‘Makespan’ (total time to complete all tours) as the primary indicator for stability analysis, as it captures the aggregate impact of all delays and operational variances.

We examined the cumulative average Makespan across three distinct operational intensities: high-stress (TO/V $= 0.3$), transitional (TO/V $=$ 0.5), and baseline (TO/V $= 1.0$).

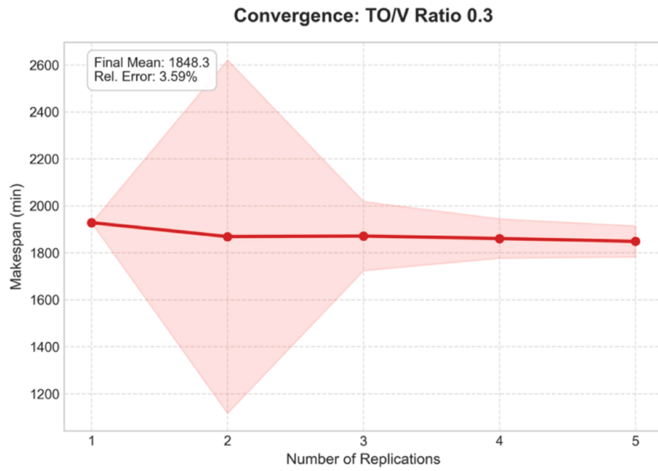
As illustrated in Fig. 10 and detailed in Table 4, the simulation outputs stabilize rapidly with the increase in the number of replications. In the baseline scenario (TO/V $= 1.0$), the system is highly stable with a relative margin of error of only 0.45%. In high-stress scenarios (TO/V $=$ 0.3), where heavy queuing occurs, the relative error remains low at 3.59%. The highest variance was observed at the transitional ratio of 0.5 (5.51% relative error); this is expected behavior in queuing systems operating near capacity, where small stochastic changes can temporarily spike queue lengths.

However, even in the highest variance cases, the 95% confidence interval half-width (66.3 min) is negligible compared to the magnitude of differences between scenarios (e.g., the difference between Ratio 0.3 and Ratio 0.5 is over 1,200 min). Consequently, five replications provide sufficient statistical power to robustly distinguish between the performance of different fleet sizing strategies. Moreover, in our sensitivity analysis reported below, we show that increasing the number of replications, even by a factor of four, does not result in significant changes in the KPIs.

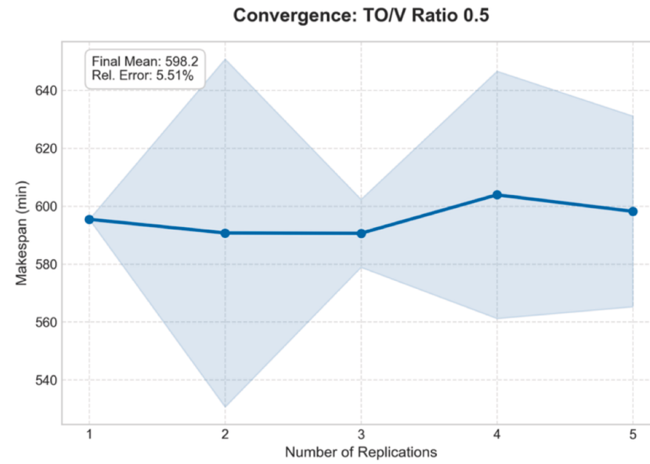
Sensitivity analysis

We performed 360 simulation scenarios with a wide range of plausible input parameters to explore the main factors influencing the operational performance of teleoperated road freight transport. To demonstrate the robustness of the simulation results against variations in input parameters, we conduct a sensitivity analysis and summarize the results in this section. We select four variables for sensitivity analysis: market penetration rate (to demonstrate scalability), number of replications (to demonstrate statistical stability), short rest duration, and teleoperator takeover time (to show the impacts of operational constraints).

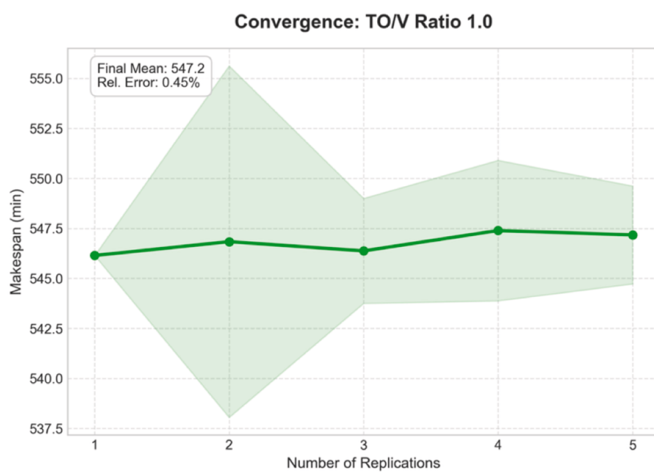
As shown in Table 5, with 100% and 200% increases in market penetration rate as well as 100% and 300% increases in the number of replications, the results remain robust, confirming stability and scalability of the system. A 50% increase in short rest duration yields moderately higher delay, average queue time, and makespan, which is expected given the additional time teleoperators spend resting. A substantially higher takeover time (5 min, representing a 67–250% increase from baseline scenarios) causes moderately higher delay and makespan with lower magnitude increases in average queue times, since the additional time in this case is primarily attributable to longer takeover procedures rather than queueing. However, the magnitude of these



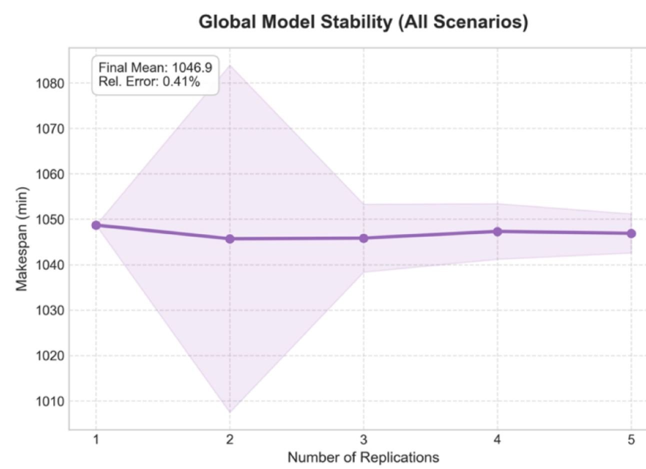
a) TO/V ratio of 0.3



b) TO/V ratio of 0.5



c) TO/V ratio of 1.0



d) Average (of all ratios)

Fig. 10. Convergence of cumulative average Makespan across varying teleoperator-to-vehicle ratios.

Table 4
Statistical Stability Analysis of Simulation Makespan (Five Replications).

Scenario (TO/V)	Operational State	Mean Makespan (Min)	Std. Dev	95% Ci Half-Width	Relative Error (%)
0.3	High Stress	1848.3	53.4	± 66.3	3.59%
0.5	Transition Phase	598.2	26.5	± 32.9	5.51%
1	Baseline (No Queues)	547.2	2	± 2.5	0.45%
Average	Global System	1046.9	10.1	± 12.5	1.41%

changes remains relatively small for large-scale service provider operations, confirming that the main findings hold across reasonable parameter ranges.

Conclusion and future research

The TO/V ratio is a crucial factor for the evaluation of the business case of teleoperated truck transport in logistics operations. The benefits of teleoperation increase when the capacity of teleoperators can be efficiently utilized by switching from an idle vehicle to another vehicle that is ready to move. This leads to higher utilization rates of teleoperators, thereby making it possible to operate a fleet of vehicles with TO/V ratios lower than one. However, when the number of teleoperators is lower than the number of vehicles, anytime a vehicle needs to move, it might need to wait in the queue before a teleoperator is assigned to it. This means there is a trade-off between the utilization rate of teleoperators, which represents the labor cost of teleoperated driving, and the waiting time for teleoperators, which represents the service level of teleoperated driving service.

In this study, we developed the first simulation framework for teleoperated fleet management in road freight transport to explore the trade-offs between the TO/V ratio and the level of service in logistics operations employing. Our simulation results indicated that the optimal TO/V ratio is dependent on the fleet size, operating hours, and the required level of service. We showcased the potential of our simulation framework for defining the optimal TO/V ratio given any service level defined by any KPI. By means of a case study that utilizes the freight transport trips within the region of South Holland in the Netherlands,

Through systematic exploration of 360 scenarios, we showed that with a teleoperation market penetration rate of 1%, a TO/V ratio of 0.6 is sufficient to meet all demand and guarantee no delay compared to the baseline makespan assuming negligible takeover times, which shows great potential for economic viability of teleoperated driving in road freight operations by significantly improved fleet management. Moreover, we showed that with a TO/V ratio of 0.5, and a standard 9-hour work shift, more than 95% of tour distances are completed and the

Table 5
Sensitivity Analysis Summary.

Parameter Variation	Delay (minutes)	DCR	Makespan (minutes)	AVG Queue Time (minutes)
Reference: Market penetration = 0.01 Replications = 5 Short rest = 10 min Take over time = 1 min TO/V = 0.5	0.0202	0.9973	561.0174	3.6200
Market penetration = 0.02	0.0146	0.9985	558.4047	2.5620
Market penetration = 0.03	0.0148	0.9985	561.6888	2.5540
Replications = 10	0.0179	0.9978	558.2126	3.0980
Replications = 20	0.0158	0.9981	558.1216	2.6785
Short rest = 15 min	0.0446	0.9926	580.9090	6.7300
Take over time = 5 min	0.0570	0.9850	622.2423	5.5040

system must only bear the burden of fewer than 10 min of waiting time on average. This confirms great promise for a positive business case for the concept of teleoperated driving as a service. In addition, we quantified the potential benefits of using teleoperation in our simulation scenarios. For teleoperated taxi fleets, (D'Orey et al., 2016) predicts 27% taxi driver labor reduction using an empirical analysis with aggregate numbers. Our findings are more optimistic, possibly due to the detailed simulation of every teleoperator and every trip with exact rest times and the different nature of freight trips, which involves less pronounced peak periods and more vehicle idling, all providing opportunities to use teleoperator time more efficiently.

We showed that tours (thereby demand for teleoperation) are not evenly distributed during working hours. In this study, we showed how to minimize teleoperator queue times by defining optimal TO/V ratios based on simulation results. An alternative approach for dealing with the peak demand issue is dynamic resource (teleoperator) allocation to maximize teleoperator utilization, which is a promising future research direction.

It is noteworthy that this study uses data and context from the South Holland region, which has specific characteristics: a diverse logistics landscape with ports and distribution centers, a composition of small and medium-sized metropolitan areas as well as rural areas, high-quality physical and digital infrastructure, a dense road network, and a shortage of truck drivers. These features make South Holland a suitable region for early adopters of teleoperated logistics services. However, other regions with different infrastructure quality, labor market conditions, or traffic patterns may impose different requirements and challenges, which limits the generalizability of the results presented in this study. Nevertheless, the results provide a useful benchmark for early adoption, and the simulation framework presented is applicable to other regions given appropriate data.

As the first simulation study to explore teleoperated road freight transport, we necessarily made strategic choices about which factors to investigate. We prioritized the most critical variables affecting system performance and applied realistic assumptions based on current regulations and practices for other parameters. While our extensive scenario analysis provides comprehensive initial insights, we acknowledge that additional factors, such as alternative fatigue management strategies, different regulatory frameworks, or other operational considerations may also influence teleoperation outcomes and merit future investigation. Moreover, this study focuses on labor costs as the primary economic driver. Other delay-related costs (e.g., parking fees, late delivery penalties) may influence the net benefits of teleoperation, particularly at low TO/V ratios, and merit comprehensive investigation in future studies. In addition, the environmental impacts of teleoperation including the potential for changes in emissions and vehicle fleet utilization impacts are important topics for the future research agenda.

Two other interesting future research directions stem from considering the idea of 24-hour operation of teleoperation centers. First, the current tour planning/scheduling paradigm assumes that human drivers control trucks, and they have restrictions in terms of operating hours and conditions. However, with teleoperation centers providing continuous service around the clock for 24 h, these restrictions can change or be eliminated. Fewer constraints for tour scheduling means better schedules. Future studies can leverage this benefit to propose new tour planning methods.

Another new possibility is coordinating teleoperation centers from different time zones. Since with teleoperated driving, there is no need for the vehicle and the teleoperator to be in the same time zone, teleoperation centers can be located in different time zones to provide 24/7 teleoperated driving service without the need for teleoperators to work overtime or outside the standard working hours. Such business models are currently in use for call centers, technical support, and customer service centers. This can lead to significant reductions in delivery times, but it requires a completely different planning paradigm. One that is not restrained by the driver's need for rest and sleep yet is still bound by the availability of the other actors in supply chains that interact with trucks and drivers (e.g., terminals, ports, storing and distribution facilities, end customers, etc.). Moreover, offering such services requires special attention to and safeguarding against potential cybersecurity and liability issues, which are among the main adoption barriers of TOD.

Another important topic related to teleoperated driving in logistics operations is the non-driving responsibilities of the drivers. Truck drivers are usually responsible for the vehicle, cargo, and communications with other supply chain actors as well as other road users and sometimes customers. Taking the driver out of the vehicle means these responsibilities need to be fulfilled by automation, digitalization, or other supply chain actors. A preliminary exploration of these responsibilities and viable solutions for overseeing them is provided in (Deckers, Madadi and Verduijn, 2021). However, these are still open research questions and require further investigation.

CRediT authorship contribution statement

Bahman Madadi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ali Nadi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Gonçalo Homem de Almeida Correia:** . **Thierry Verduijn:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Lóránt Tavasszy:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

The pseudocode for the teleoperated freight transport simulation is provided below.

Step	Action
1. Initialization	
1.1	Load freight tour data and define simulation parameters (teleoperator-vehicle ratio, takeover time, work shift duration, rest periods)
1.2	Sample tours based on market penetration rate and apply random departure delays
1.3	Create vehicle entities with activity sequences: Buffer → Queue → Takeover → Teleoperation
1.4	Create teleoperator entities based on teleoperator-vehicle ratio
1.5	Initialize event list, queue, and simulation clock
2. Event Processing Loop	
2.1	Extract earliest event from event list and advance simulation clock
2.2	Process event according to type:
	Buffer Event: Vehicle waits in buffer, then proceeds to queue
	Queue Event (begin):
	Search for idle teleoperator
	If available: assign teleoperator to vehicle immediately
	Otherwise: add vehicle to waiting queue
	Queue Event (end): Remove vehicle from queue, record waiting time, proceed to takeover
	Takeover Event: Teleoperator prepares for control transfer (fixed duration), then begins teleoperation
	Teleoperation Event:
	Execute freight trip under remote control
	Upon completion: release teleoperator to rest period
	Rest duration depends on trip length (short rest for trips $\leq$ 4.5 h, long rest otherwise)
	Rest Event (end):
	Teleoperator becomes available
	If queue is non-empty: assign next waiting vehicle
	Otherwise: return to idle state
2.3	Generate and schedule next event based on activity sequence
2.4	Update event list and maintain chronological order
2.5	Track system state (vehicle status, teleoperator status, queue length, utilization metrics)
2.6	Repeat until all vehicles complete their tours
3. Output	
3.1	Calculate performance metrics: average waiting times, resource utilization rates, tour completion rates, and system delays
3.2	Repeat simulation for multiple replications with different random seeds
3.3	Aggregate results across parameter scenarios

Data availability

The data and code are available via the following repository: https://github.com/bahmanmdd/TOD_simulation

References

Boban, M., Kousaridas, A., Manolakis, K., Eichinger, J. and Xu, W. (2018) "Connected Roads of the future: Use cases, requirements, and design considerations for vehicle-to-everything communications," *IEEE Vehicular technology magazin*, 13(3), pp. 110–123. Available at: https://doi.org/10.1109/MVT.2017.2777259.

de Bok, M. and Tavasszy, L. (2018) "An empirical agent-based simulation system for urban goods transport (MASS-GT)," *Procedia Computer Science*, 130, pp. 126–133. Available at: https://doi.org/10.1016/j.procs.2018.04.021.

de Bok, M., Tavasszy, L., Bal, I., Thoen, S., 2018. "The incremental development path of an empirical agent-based simulation system for urban goods transport (MASS-GT)," in. World Conference on Transport Research, Transportation Research Procedia. Available at. https://www.researchgate.net/profile/Michiel-De-Bok-2/publication/333609988_The_incremental_development_path_of_an_empirical_agent-based_simulation_system_for_urban_goods_transport_MASS-GT-review_under_responsibility_of_WORLD_CONFERENCE_ON_TRANSPORT_RESEARCH_SOCIETY/links/5cf6845992851c4dd029c8d0/The-incremental-development-path-of-an-empirical-agent-based-simulation-system-for-urban-goods-transport-MASS-GT-review-under-responsibility-of-WORLD-CONFERENCE-ON-TRANSPORT-RESEARCH-SOCIETY.pdf.

de Bok, M., Tavasszy, L., Kourounioti, I., Thoen, S., Eggers, L., Nielsen, V., Streng, J., 2021. Application of the HARMONY tactical freight simulator to a case study for zero emission 2 zones in Rotterdam. Available at: Transportation Research Records 2675 (10) https://harmony-h2020.eu/wp-content/uploads/2021/11/2021.01_-TRB_Application-of-the-HARMONY-tactical-freight-simulator-for-a-case-study-for-zero-emission-zones-in-Rotterdam_TUD.pdf.

de Bok, M., Tavasszy, L., and Sebastiaan Thoen (2022) "Application of an empirical multi-agent model for urban goods transport to analyze impacts of zero emission zones in The Netherlands," *Transport Policy*, 124, pp. 119–127. Available at: https://doi.org/10.1016/j.tranpol.2020.07.010.

Boker, A., Grimberg, E., Tener, F. and Lanir, J. (2025) "Navigating the Last Mile: A Stakeholder Analysis of Delivery Robot Teleoperation," *Sustainability*, 17(13), p. 5925. Available at: https://doi.org/10.3390/su17135925.

Chen, Z., He, F., Zhang, L. and Yin, Y. (2016) "Optimal deployment of autonomous vehicle lanes with endogenous market penetration," *Transportation Research Part C: Emerging Technologies*, 72, pp. 143–156. Available at: https://doi.org/10.1016/j.trc.2016.09.013.

De Jong, G. (2007) *VALUE OF FREIGHT TRAVEL-TIME SAVINGS. IN: HANDBOOK OF TRANSPORT MODELLING*. Available at: https://trid.trb.org/View/677920 (Accessed: May 12, 2025).

Deckers, L., Madadi, B., Verduijn, T., 2021. Tele-operated-driving-in-logistics-as-a-transition-to-full-automation-An-exploratory-study-and-research-agenda. In. *27th ITS Worlds Congress*.

D'Orey, P.M., Hosseini, A., Azevedo, J., Diermeyer, F., Ferreira, M. and Lienkamp, M. (2016) "Hail-a-Drone: Enabling teleoperated taxi fleets," in *IEEE Intelligent Vehicles Symposium*, pp. 774–781. Available at: https://doi.org/10.1109/IVS.2016.7535475.

EUR-Lex-02006R0561-20200820 (2020). Available at: https://eur-lex.europa.eu/eli/reg/2006/561/2020-08-20/eng (Accessed: May 12, 2025).

Favarò, F., Eurich, S. and Nader, N. (2018) "Autonomous vehicles' disengagements: Trends, triggers, and regulatory limitations," *Accident Analysis and Prevention*, 110, pp. 136–148. Available at: https://doi.org/10.1016/j.aap.2017.11.001.

Gnatzig, S., Chucholowski, F., Tang, T. and Lienkamp, M. (2013) "A system design for teleoperated road vehicles," in *Proceedings of the 10th International Conference on Informatics in Con trol, Automation and Robotics*, pp. 231–238. Available at: https://doi.org/10.5220/0004475802310238.

Goodall, N. (2020) "Non-technological challenges for the remote operation of automated veh icles," *Transportation Research Part A: Policy and Practice*, 142(September), pp. 14–26. Available at: https://doi.org/10.1016/j.tra.2020.09.024.

Hjelt, T. (2021) *Cost-Effectiveness of 5G Teleoperated Automated Buses*. Åbo Akademi University. Available at: https://www.doria.fi/handle/10024/180914 (Accessed: May 12, 2025).
Hofbauer, M., Kuhn, C.B., Petrovic, G., Steinbach, E., 2020. In: TELECARLA: an Open Source Extension of the CARLA Simulator for Teleope Rated Driving Research Using off-the-Shelf Components. IEEE, Las Vegas, NV, USA. https://doi.org/10.1109/IV47402.2020.9304676.
Ji-Hyland, C. and Allen, D. (2022) "What do professional drivers think about their profession? An examination of factors contributing to the driver shortage," *International Journal of Logistics Research and Applications*, 25(3), pp. 231–246. Available at: https://doi.org/10.1080/13675567.2020.1821623.
de Jong, G., Burgess, A., Tavasszy, L., Versteegh, R., de Bok, M., de Bok, N., 2011. Distribution and Modal Split Models for Freight Transport in the Netherlands. Association For European Transport and Contributors.
de Jong, G., Kouwenhoven, M., Bates, J., Koster, P., Verhoef, E., Tavasszy, L. and Warffemius, P. (2014) "New SP-values of time and reliability for freight transport in the Netherlands," *Transportation Research Part E: Logistics and Transportation Review*, 64, pp. 71–87. Available at: https://doi.org/10.1016/j.tre.2014.01.008.
Law, A.M. (2017) "A tutorial on design of experiments for simulation modeling," in *2017 Winter Simulation Conference (WSC)*. *2017 Winter Simulation Conference (WSC)*, pp. 550–564. Available at: https://doi.org/10.1109/WSC.2017.8247814.
Lopane, F., Kamargianni, M., Yfantis, L., Chaniotakis, E., Pappelis, D., Fermi, F., Batty, M., de Bok, M., Tavasszy, L., Tsirimpa, A., Tsouros, I., Polydoropoulou, A., Georgakis, P., Angelica, S., Djukic, T., Bothos, E. and Magoutas, B. (2021) *HARMONY Model Suite: an integratedspatial and multimodal transport planning tool to lead a sustainable transition to a new mobility era.*, *ETC Conference Papers 2020*. *European Transport Conference 2020*, Milan (Italy): Association For European Transport. Available at: https://aetransport.org/past-etc-papers/conference-papers-2020?abstractId=7049&state=b (Accessed: May 12, 2025).
Lv, C., Cao, D., Zhao, Y., Auger, D.J., Sullman, M., Wang, H., Dutka, L.M., Skrypchuk, L. and Mouzakitis, A. (2018) "Analysis of autopilot disengagements occurring during autonomous vehic le testing," *IEEE/CAA Journal of Automatica Sinica*, 5(1), pp. 58–68. Available at: https://doi.org/10.1109/JAS.2017.7510745.
Madadi, B., Nes, R., Snelder, M., Arem, B., 2021. "Multi-stage optimal design of road networks for automated vehicles with elastic multi-class demand," *Computers and Operations Research*, 136. Available at: https://doi.org/10.1016/j.cor.2021.105483.
Madadi, B., Nes, R., Snelder, M. and Arem, B. (2020) "A bi-level model to optimize road networks for a mixture of manual and automated driving: An evolutionary local search algorithm," *Computer-Aided Civil and Infrastructure Engineering*, 35(1), pp. 80–96. Available at: https://doi.org/10.1111/mice.12498.
Madadi, B., Nes, R., Snelder, M. and Arem, B. (2021b) "Optimizing Road Networks for Automated Vehicles with Dedicated Links , Dedicated Lanes , and Mixed-Traffic Subnetworks," *Journal of Advanced Transportation*, 2021, pp. 1–17. Available at: https://doi.org/10.1155/2021/8853583.
Milakis, D., Arem, B., Wee, B., 2017. "Policy and society related implications of automated driving: a revie w of literature and directions for future research," *Journal of Intelligent Transportation Systems*, 2450 (February). Available at: https://doi.org/10.1080/15472450.2017.1291351.
Mohammed, R.A., Nadi, A., Tavasszy, L. and Bok, M. de (2023) "Data Fusion Approach to Identify Distribution Chain Segments in Freight Shipment Databases," *Transportation Research Record*, 2677(6), pp. 310–323. Available at: https://doi.org/10.1177/03611981221147049.
Neumeier, S., Gay, N., Dannheim, C., Facchi, C., 2018. On the way to Autonomous Vehicles Teleoperated Driving. In: *AmE 2018-Automotive Meets Electronics*, 9th GMM-Symposium,. VDE, Dortmund, Germany, pp. 49–54.
Neumeier, S., Hopp, M. and Facchi, C. (2019) "Yet another driving simulator OpenROUTS3D: The driving simulator for teleoperated driving," in *2019 8th IEEE International Conference on Connected Vehicles and Expo, ICCVE 2019 - Proceedings*, pp. 0–5. Available at: https://doi.org/10.1109/ICCVE45908.2019.8965037.
Sargent, R.G. (2013) "An introduction to verification and validation of simulation models," in *2013 Winter Simulations Conference (WSC)*. *2013 Winter Simulations Conference (WSC)*, pp. 321–327. Available at: https://doi.org/10.1109/WSC.2013.6721430.
Schuster, A.M., Agrawal, S., Britt, N., Sperry, D., Van Fossen, J.A., Wang, S., Mack, E.A., Liberman, J. and Cotten, S.R. (2023) "Will automated vehicles solve the truck driver shortages? Perspectives from the trucking industry," *Technology in Society*, 74, p. 102313. Available at: https://doi.org/10.1016/j.techsoc.2023.102313.
Tapia, R.J., Kourounioti, I., Thoen, S., de Bok, M. and Tavasszy, L. (2023) "A disaggregate model of passenger-freight matching in crowdshipping services," *Transportation Research Part A: Policy and Practice*, 169, p. 103587. Available at: https://doi.org/10.1016/j.tra.2023.103587.
Thoen, S., Tavasszy, L., de Bok, M., Correia, G. and van Duin, R. (2020) "Descriptive modeling of freight tour formation: A shipment-based approach," *Transportation Research Part E: Logistics and Transportation Review*, 140, p. 101989. Available at: https://doi.org/10.1016/j.tre.2020.101989.
Verduijn, T., Madadi, B., Deckers, L. and Camps, P. (2021) *5G-Blueprint D3.1: Business cases and initial value network*. HZ University of Applied Sciences, pp. 1–158. Available at: https://www.5gblueprint.eu/wp-content/uploads/2021/05/D3.1_v2.pdf.
Veryard, D., Aronietis, R., Poggi, R., Viegas, J., 2017. *Managing the transition to Driverless Road Freight Transport*. International Transport Forum (ed.). Available at: https://www.itf-oecd.org/sites/default/files/docs/managing-transition-driverless-road-freight-transport.pdf.
Winfield, A.F.T., 2000. Future-Directions-in-Tele-operated-Robotics. Telerobotic applications, Available at: https://www.researchgate.net/profile/Alan-Winfield/publication/267260583_Future_Directions_in_Tele-operated_Robotics/links/54746ec10cf2778985abdd35/Future-Directions-in-Tele-operated-Robotics.pdf.
de Winter, J., Driessen, T., Dodou, D., Cannoo, A., 2024. "Exploring the challenges faced by dutch truck drivers in the era of technological advancement," *Frontiers in Public Health*, 12. Available at: https://doi.org/10.3389/fpubh.2024.1352979.