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Multi-Agent Simulation of a Demand-Responsive Transit System Operated by Autonomous Vehicles

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Abstract

Shared mobility solutions improve traffic efficiency in cities. This paper addresses the design of an urban demand-responsive transit system operated by a fleet of autonomous modules as a public transportation service. We introduce a discrete event-based multi-agent simulation to reflect system dynamics at an operational level. Vehicles, customers, and intelligent stops are modeled as software agents. Each entity has its own decision-making and planning component. Vehicles compete for a limited number of order requests, and decentralized stops manage the matching between a customer and a prospective vehicle. Scheduling and routing events take place highly dynamically. A simulation study evaluates a demand-responsive operation as a replacement for a fixed-route bus service. Results show that a total demand of 2.3 million rides can be fulfilled with a fleet of around 43,000 six-seater modules. In comparison with the current bus system, the total energy consumption and the system's utilization are improved, while transport times and distances result in values below the bus system's performance and therefore must be optimized in further research.

With the ongoing urbanization and continuous growth of the world's megacities, the demand for mobility increases. Urban transportation is becoming a significant challenge for the future. In order to reduce road congestion and commuting times as well as improve customer service, the focus is shifting toward new technologies and mobility concepts (*1*). Autonomous electric vehicles will transport customers efficiently and effectively in a connected environment (*2*). To further reduce the number of vehicles, car- and ridesharing approaches are being pursued, and mobility is becoming more and more of a service than an individual good.

While traditional public transit typically has fixed routes and schedules, demand-responsive transit (DRT) operates more flexibly (*3*). Schedules in a dial-a-ride application result from immediate or advance bookings (*4*). Route planning is done dynamically based on given requests. Until now, DRT has been focused on areas with low demand where fixed-route and fixed-schedule bus services face profitability issues. Common applications offer specialized transportation services for customers, feeder services to fixed-route systems, and flexible-route segment or route-deviation services (*5*). In the United States, DRT systems are mostly used as a paratransit service for people with limited mobility (*6*). Origin–destination patterns vary between many-to-many, many-to-few, many-to-one, few-to-many, and few-to-few relationships (*5*). Transport tasks can be served directly without any transfer or detour, or without transfers but with a possible detour due to additional stops, or by allowing transfers. The size of a DRT fleet depends on the (peak-period) demand, service and provider policies, passenger characteristics, trip pattern type, and service area characteristics (*5*).

The decision-making between fixed- and demand-oriented systems depends on the specific use case. Edwards and Watkins (*7*) introduce a methodology to compare fixed and DRT operation modes for a feeder system. Shen et al. (*8*) investigate an autonomous vehicle DRT system as a last mile solution. Schofer et al. (*6*) present a planning tool to derive fleet requirements for DRT applications. Noda et al. (*9*) evaluate the efficiency of a dial-a-ride system with that of a traditional bus system, looking at the structure of a town as well as the demand and fleet size. Mo et al. (*10*) compare various pricing policies and vehicle scheduling mechanisms for a shared dial-a-ride service. Jung and Jayakrishnan (*11*) explore a high-coverage point-to-point transit system operated by electric vehicles.

The aim of this paper is to design and analyze the performance of a public many-to-many DRT system with real-time scheduling operated on a city scale by fully-autonomous modules.

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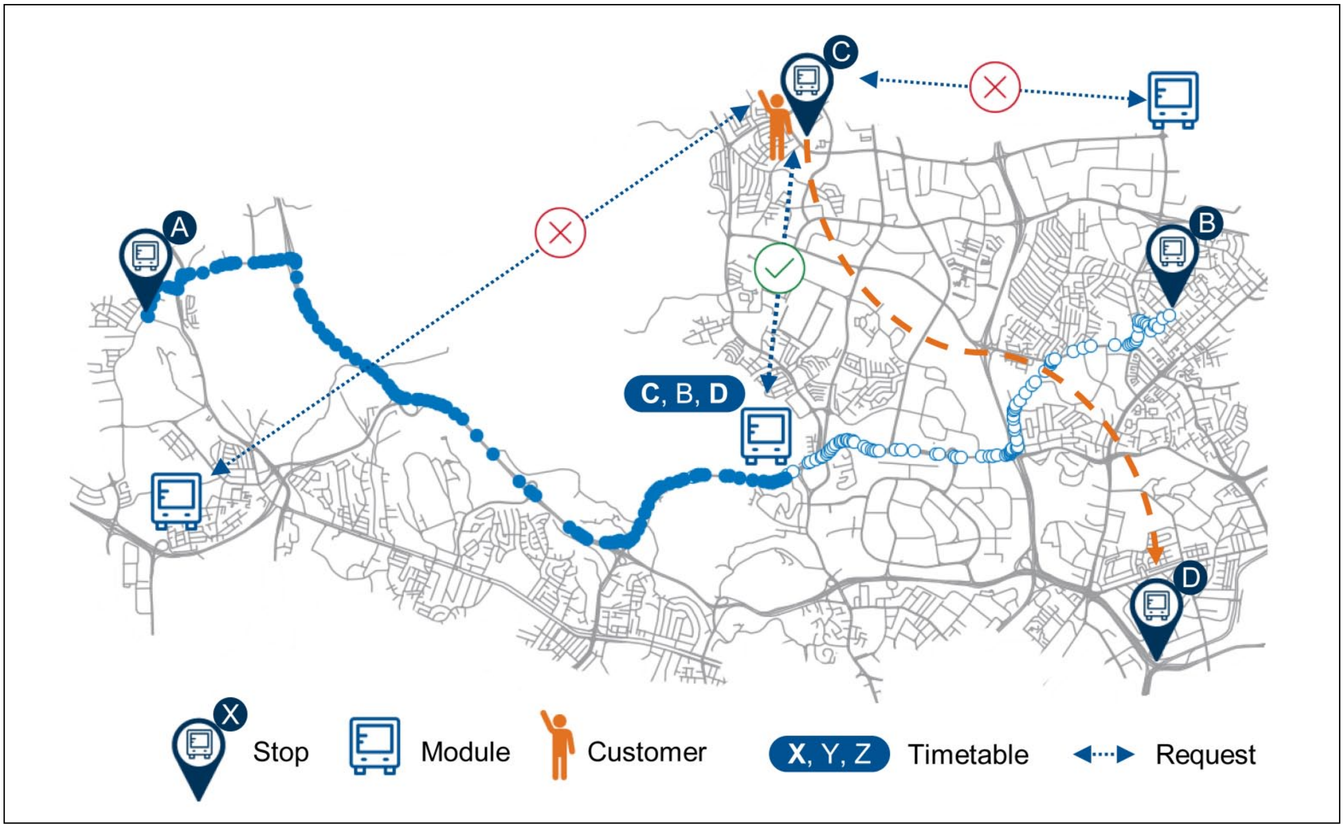

Figure 1. Customer–module matchmaking.

DRT in Terms of the Vehicle Routing Problem

Vehicles in a DRT system do not follow pre-defined routes. In Operations Research literature, the determination of the optimal set of routes for a fleet of vehicles that serves a set of distributed customers is described as the vehicle routing problem (VRP). Eksioglu et al. (*12*) provide a taxonomic overview including a categorization for the existing research on VRPs.

A DRT system can be categorized as a dial-a-ride problem with a time window, which is a specific form of the VRP. The objective is to minimize the total cost for a fixed number of vehicles with given capacities that must serve a set of dispersed customers within a specific time window (*13*).

The VRP can be addressed using a static or dynamic approach. The static case describes an optimization problem in which all requests for the entire time are known before the beginning of the service. Due to its non-deterministic polynomial-time harness in computational complexity theory, it is not possible to solve a larger problem within a given time frame with a reasonable computational effort (*14*).

The dynamic option describes situations with vehicles already executing transport tasks. Vehicle routing and scheduling must be conducted in real time. Existing plans must be taken into account, and routes may need to be adjusted accordingly. The system tries to find the optimal solution for each new request, which is usually dispatched by a control center. However, limited fleet capacity and temporal constraints can cause delays or refusals of bookings. Well-known solutions are based on classical heuristics, metaheuristics, and matheuristics (*15*).

Concept

The following sections cover the use case definition for the proposed DRT system, its conceptional design, and further simulation-related aspects.

Use Case Definition

To operate a DRT system, a vehicle fleet is required. Its main task is to transport customers between various pickup and drop-off points. We assume a service in which vehicles have the ability to move autonomously within a given road network. Boarding and alighting take place at defined stops. Customers, intelligent stops, and modules are connected and communicate to find the best transport option. Figure 1 illustrates a typical situation.

The initial action is a service request submitted by a customer at a stop without an advance-notice requirement. The stop organizes the ride for the customer by contacting several modules. It serves as a decentralized dispatcher and assigns the transportation task to exactly one module. This module

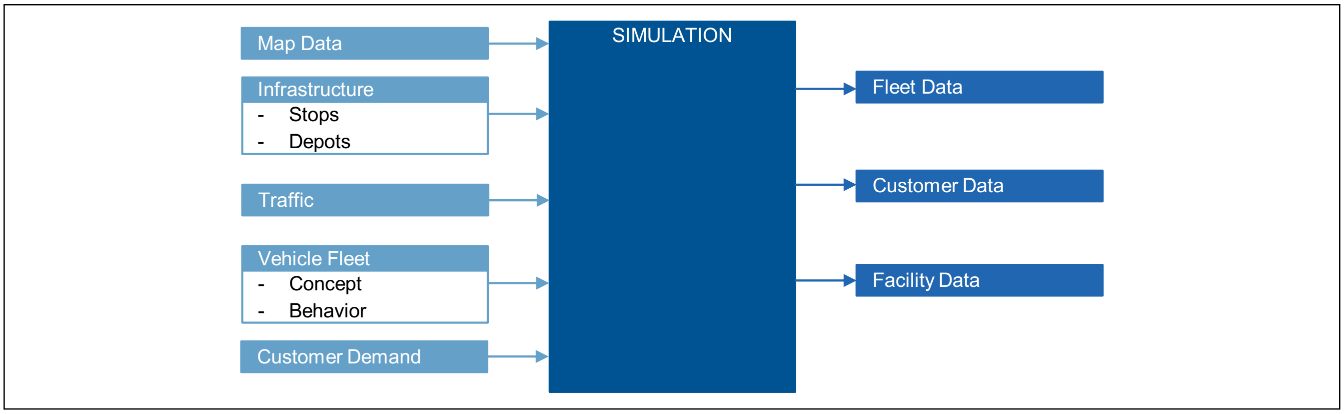

Figure 2. Input and output interfaces.

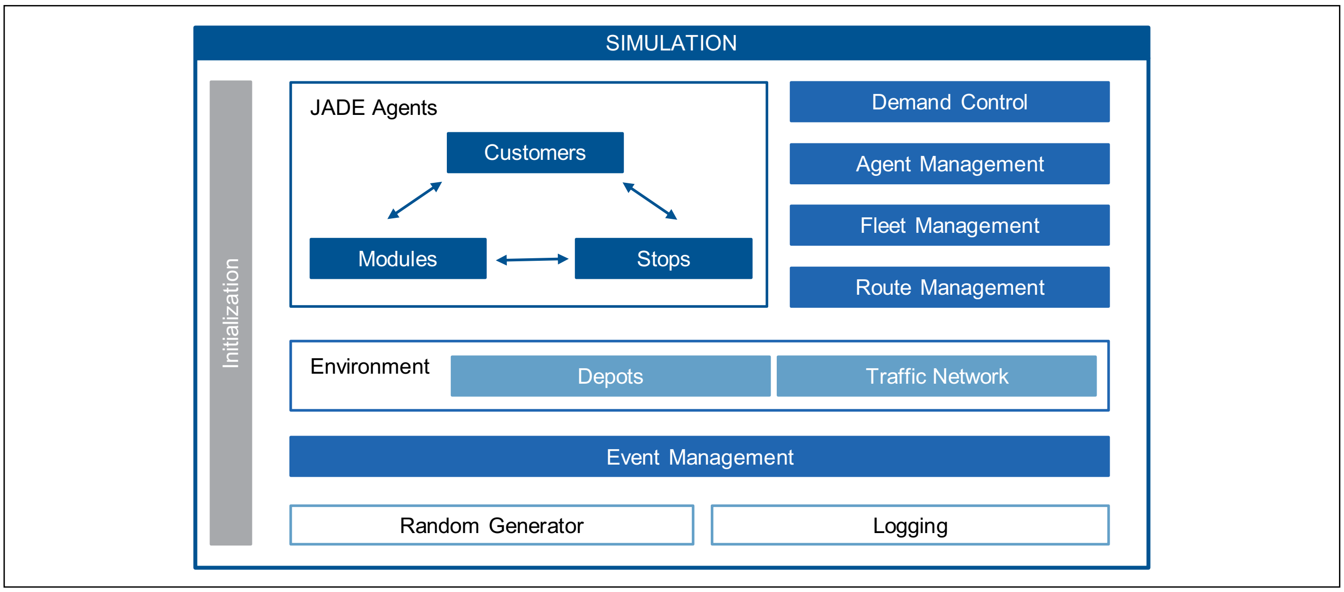

Figure 3. Design of the internal structure.

incorporates the job into its route planning. When a module has finished its schedule, it returns to a depot.

The decision to realize a stop-to-stop operation is made for several reasons. At first sight, it is more convenient for customers to order a door-to-door transportation service. However, including stops in a dial-a-ride system also has advantages. Stiglicet et al. (*16*) state that meeting points can increase the number of matched participants in a ridesharing application and reduce the total driven distance of the fleet. Additionally, stops allow several boarding and alighting actions to be aggregated to a single event. A proper stop design can decrease dwelling times and minimize the impact on other road users (*4*).

Simulation Approach

We introduce a multi-agent simulation to evaluate the performance of the proposed DRT system. Instead of trying to optimize the entire system at once, this approach follows the "divide and conquer" principle. Each transportation task defines a sub problem, which is solved step-by-step on an individual basis. This design has significant benefits when it comes to scalability, adaptability, and robustness.

The simulation itself is realized as a discrete event-based approach. It is written in Java, and its architecture supports multi-threading. JADE (*17*) is used as a middleware to incorporate multi-agent features. Figure 2 shows input and output interfaces.

The basic internal structure is illustrated in Figure 3. An agent management module handles the creation and destruction of agents. Since in JADE every agent is represented as an own thread, an event management module has to take over the synchronization task. A central fleet management module keeps a list of the latest agent states updated and provides this information to other entities. Navigation is organized via routing management. Additional modules are a

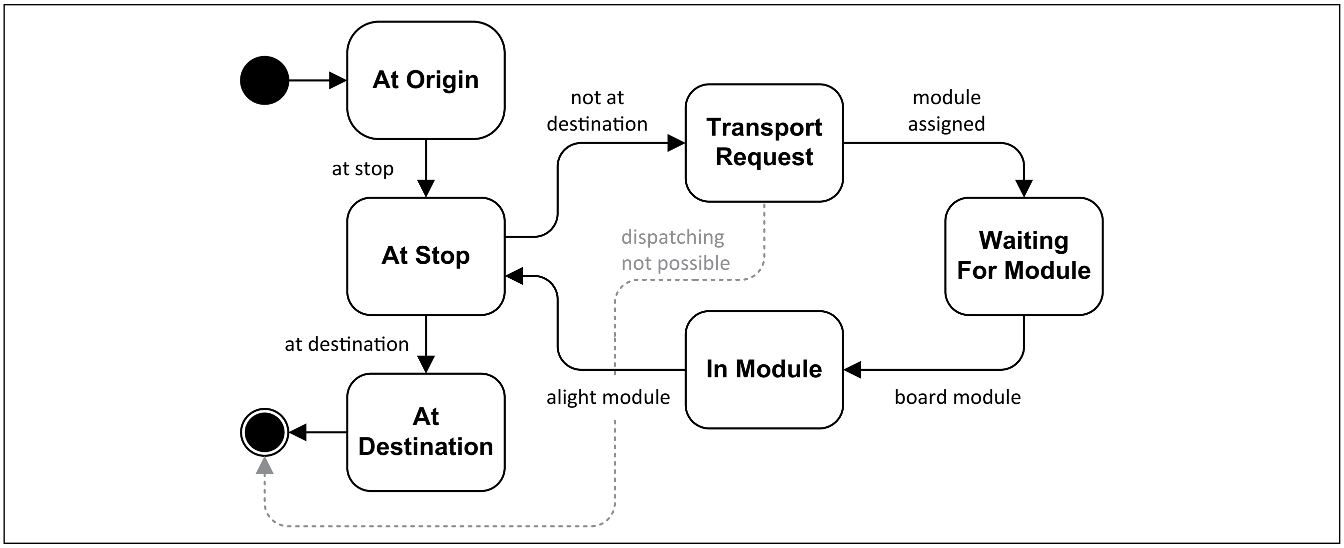

Figure 4. Customer finite state machine.

random number generator for stochastic calculations and a class for data logging. Further details about the simulation core have been published in a paper (*18*).

Customer, module, and stop agents represent active, intelligent entities. Their behavior is independent from each other and triggered by event or message calls. Dependent on the type, agents collaborate or compete for an open task. Modules are the most active components, whereas stops take over a mediator role to match customers with modules. All agents live in a shared environment consisting of depots and a traffic network. Depots provide space for the modules.

Customer: A customer agent is only temporarily in the system. It is created as soon as it submits a transport request and is removed after reaching the final destination. Its goal is to reach the target location as quickly as possible.

This requires one to request the transport at the stop and then follow the instructions of the system. A customer must wait for a module and board and alight at the required time. The customer's behavior is managed by a state machine, as shown in Figure 4.

Stop: A stop is primarily responsible for finding the best matching modules for a given transportation request. Its tasks include managing modules currently at a stop. Stops are facilities that provide transfer space but no parking space. The transfer space limits the number of vehicles that can simultaneously stop. A stop implements a timetable of planned incoming vehicles, including boarding and alighting customers. This information is used to address arriving vehicles during dispatching.

It further manages currently transferring vehicles as well as vehicles queuing at the stop. An arriving module contacts a stop which checks its available transfer space. It advises the module to either continue with the transfer or to wait in the queue. Once a previously transferring vehicle departs and the queue is not empty, the stop notifies the first waiting vehicle about the free space.

Modules: The module's main responsibility is to transport customers. This includes active bidding for offered transportation requests. Modules try to finish the remaining transportation tasks as quickly as possible by dropping all customers at their destinations and returning back to the closest depot.

Within the initialization, all modules are distributed to the depots. Whenever a module receives a request, it calculates the corresponding transportation effort and sends out a cost proposal. If a module is assigned a transport task, it incorporates it into its future planning. With the ability to transport multiple customers, the module can constantly add new customers as long as it has not reached its capacity limit.

To keep track of all customers and execute the tasks as desired, each module follows an internal plan realized as a timetable. This list includes all planned stops including arrival time and both boarding and alighting customers. Based on the timetable, the module knows exactly where and when to go next, as well as with whom to communicate. Knowing the number of boarding and alighting customers enables the module to estimate its dwelling time.

Whenever a new customer request is added to the timetable, the optimal positions for the new pickup and drop-off stop must be determined. The insertion of a stop element (Figure 5) is based on an optimization of the caused delay. It is required that the new pickup stop is added before the new drop-off stop and that the order of existing stops remains the same.

Similar to the customer agent, a module shows different behaviors and interactions depending on its state. To realize this, a finite state machine is implemented as shown in Figure 6.

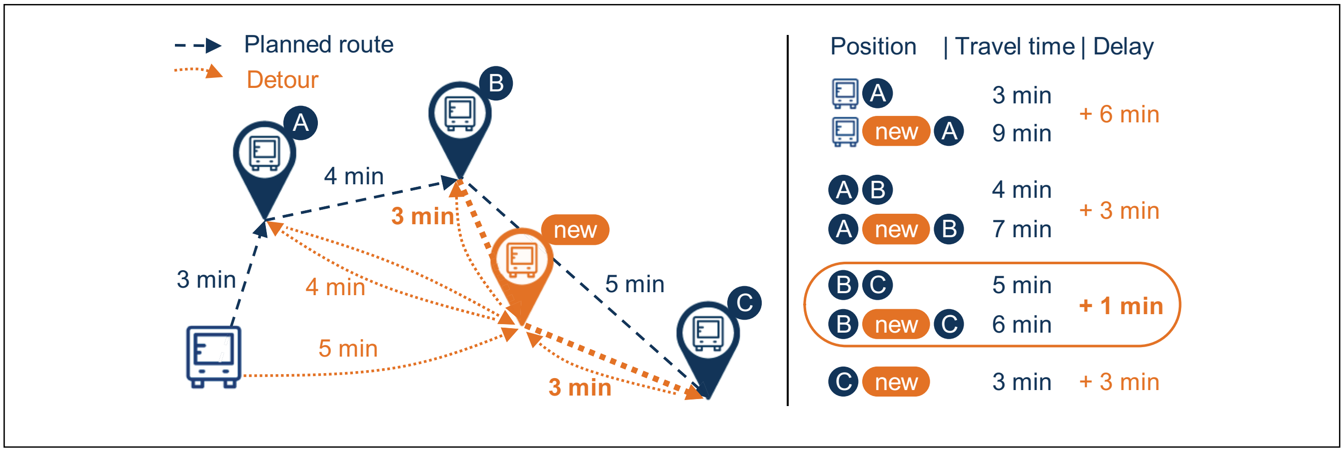

Figure 5. Decision-making to insert a new stop in given timetable.

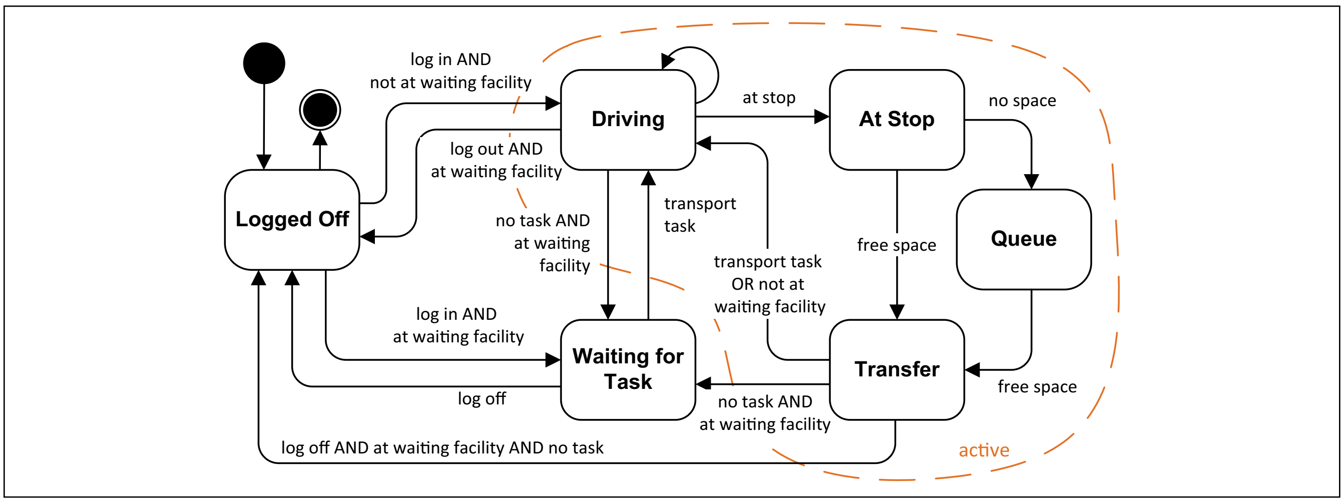

Figure 6. Module finite state machine.

The *Logged Off* state is the initial state. While *Waiting for task*, the module receives dispatching messages and participates in the competition for orders. When a job is assigned, the module becomes active. All movements happen within the state *Driving*. This includes customer transport, driving to a customer, and driving back to the depot. When arriving *At stop*, the module tries to register at the stop. Depending on the availability of free transfer space, it either directly continues with the transfer or enters the queue to wait until it receives a free space notification. The *Transfer* state defines the actual time with customers boarding and alighting.

The duration depends on vehicle, customers, and stop characteristics. At the beginning of a transfer, the module notifies all alighting passengers to exit. After completion, the vehicle deregisters from the stop. If further tasks need to be completed, it continues driving to the next planned location. Otherwise, the module checks if it can wait at the stop or if it needs to find a waiting facility.

Dispatching Communication. Dispatching causes an extensive message exchange. The communication act itself consists of two nested protocols as shown in Figure 7. An outer FIPA-Request (*19*) handles the messaging between customer and stop, and an inner FIPA Iterated Contract Net Interaction Protocol (*19*) specifies the communication between the stop and a set of modules.

First, a customer arrives at his departure stop and requests a transport to his desired destination. The stop agrees to conduct the dispatching and creates a transport job including stop-specific information. It determines modules to address and sends out a call for proposals. In order to guarantee the optimal dispatch result, all modules would need to be assessed. However, an increasing number of receivers significantly slows down the simulation performance. To minimize computational efforts and still achieve a sufficient quality, receivers are chosen heuristically in three categories, namely, surrounding vehicles, arriving vehicles, and empty vehicles.

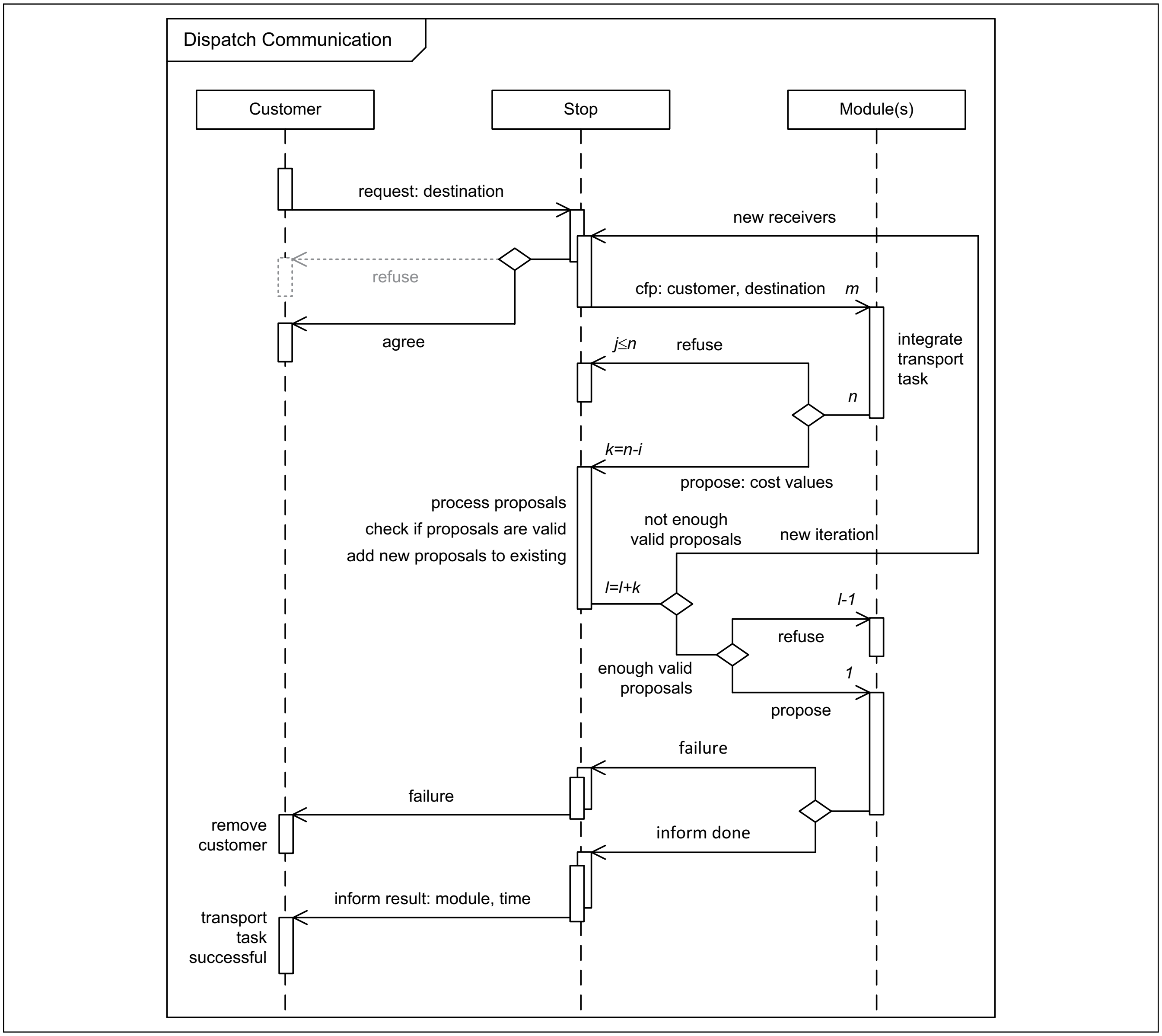

Figure 7. Dispatch communication.

This is done for several reasons. It is assumed that vehicles close to the departure stop reduce customer waiting times and empty trip distances. Modules with a stop already in their timetable might be suitable candidates as no additional detour is needed. Empty vehicles are added to the active fleet if needed. This ensures a minimum quality of service for a customer even if all surrounding modules are occupied.

Addressed modules have the option to accept or reject a given proposal. A direct rejection occurs when a module cannot provide any free space for the customer. Otherwise, they try to integrate the task into their plans and respond with a proposal that contains information about trip duration, expected waiting time, and additional energy consumption. The stop waits until it has received all responses and processes them. If the number of valid proposals is below a defined limit, the stop starts a new iteration, adding more receivers.

Having received enough proposals or when no additional vehicles remain, the stop performs a cost assessment. It calculates a final cost value for each vehicle and determines the best module. It replies to all proposals, accepting the best one and sending refusals to the others. The winning module integrates the transport job into its plan and informs the stop about its completion. If everything is successful, the stop informs the customer about the chosen module, estimated pickup time, and transport details. In case the stop is not able to find a suitable module, or a communication error occurs, the customer is informed about the failure instead.

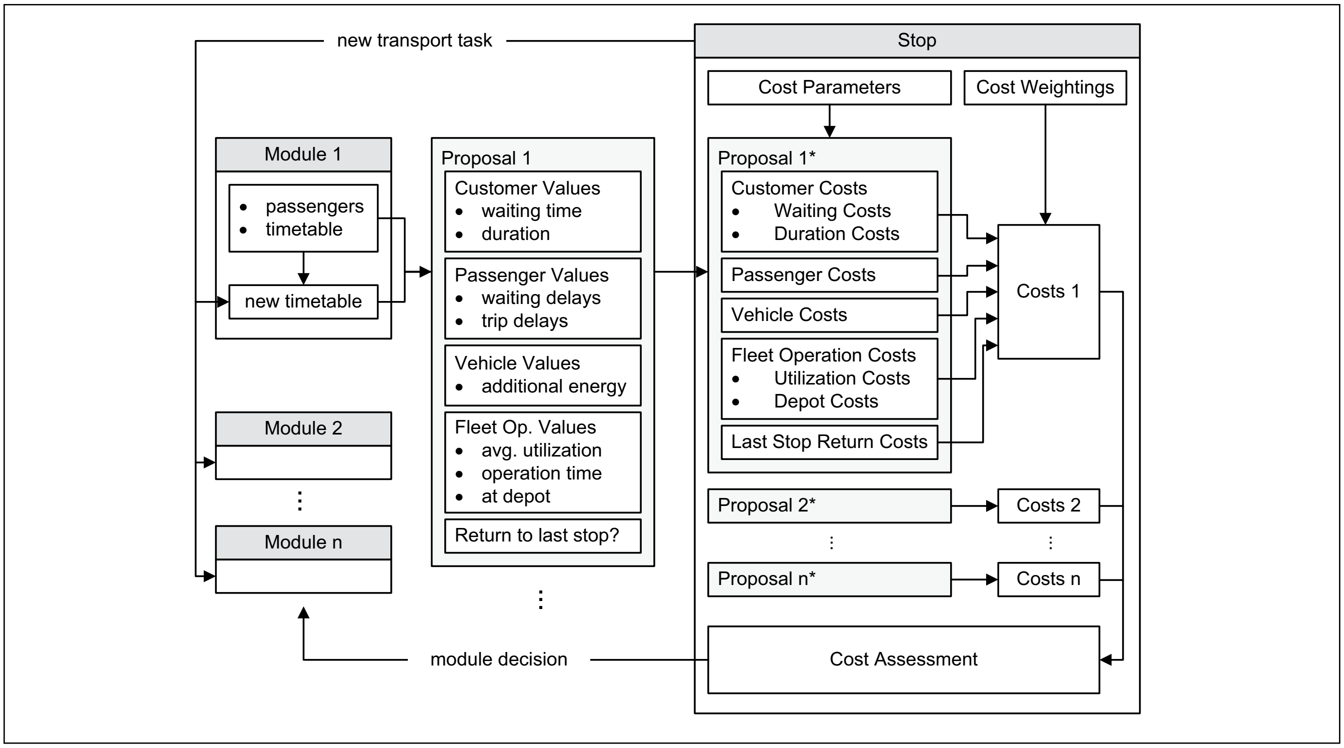

Figure 8. Cost calculation structure.

Cost Assessment

Since the cost calculation for dispatching is crucial for the DRT performance, its structure is explained in further detail. The proposed on-demand operation is only successful if it fulfills at least the minimum requirements regarding customer service and operation costs. Stakeholders have specific interests and needs. They typically ask different questions:

Customer: How long do I have to wait? How long is the travel time compared with other modes?

Passenger: How does a potential new customer affect my travel?

Vehicle: How much energy is needed to transport an additional customer?

Fleet Operation: Does the open task require the addition of a new vehicle to the active fleet?

In order to take these partially conflicting requirements into account, a trade-off has to be evaluated. The basic idea is to perform a weighted cost evaluation, as shown in Figure 8. *Customer costs* consider requirements regarding waiting time and the trip duration of a new customer. *Passenger costs* look at the same aspect, but for all passengers that are in the module or waiting at a stop. *Vehicle costs* reflect the additional energy needed for a new trip. *Fleet operation costs* aim to reduce the total number of active modules. This can be done by pulling as few new vehicles as possible from a depot and by getting active ones to return as quickly as possible. The *Last stop return costs* avoid situations in which vehicles return directly to their previous stops.

Simulation Study

To evaluate the feasibility of the proposed DRT system, a simulation study was conducted. We selected a use case in which the current bus system in Singapore is replaced by a DRT system and compared its performance. This subchapter presents the chosen input dataset and key findings.

Facilities and Road Network

The chosen infrastructure is based on current facilities in Singapore. It contains 14 bus depots and a total of 4,923 stops, including 35 hubs, 35 interchanges, and 23 terminals. The underlying road network was taken from Open Street Map and processed into a routable graph.

Demand

One of the key inputs is customer demand. To create a list of origin–destination relationships, Singapore's Land Transport Authority (LTA) provided smart card data from the year 2013. This dataset includes tap in and tap out information of

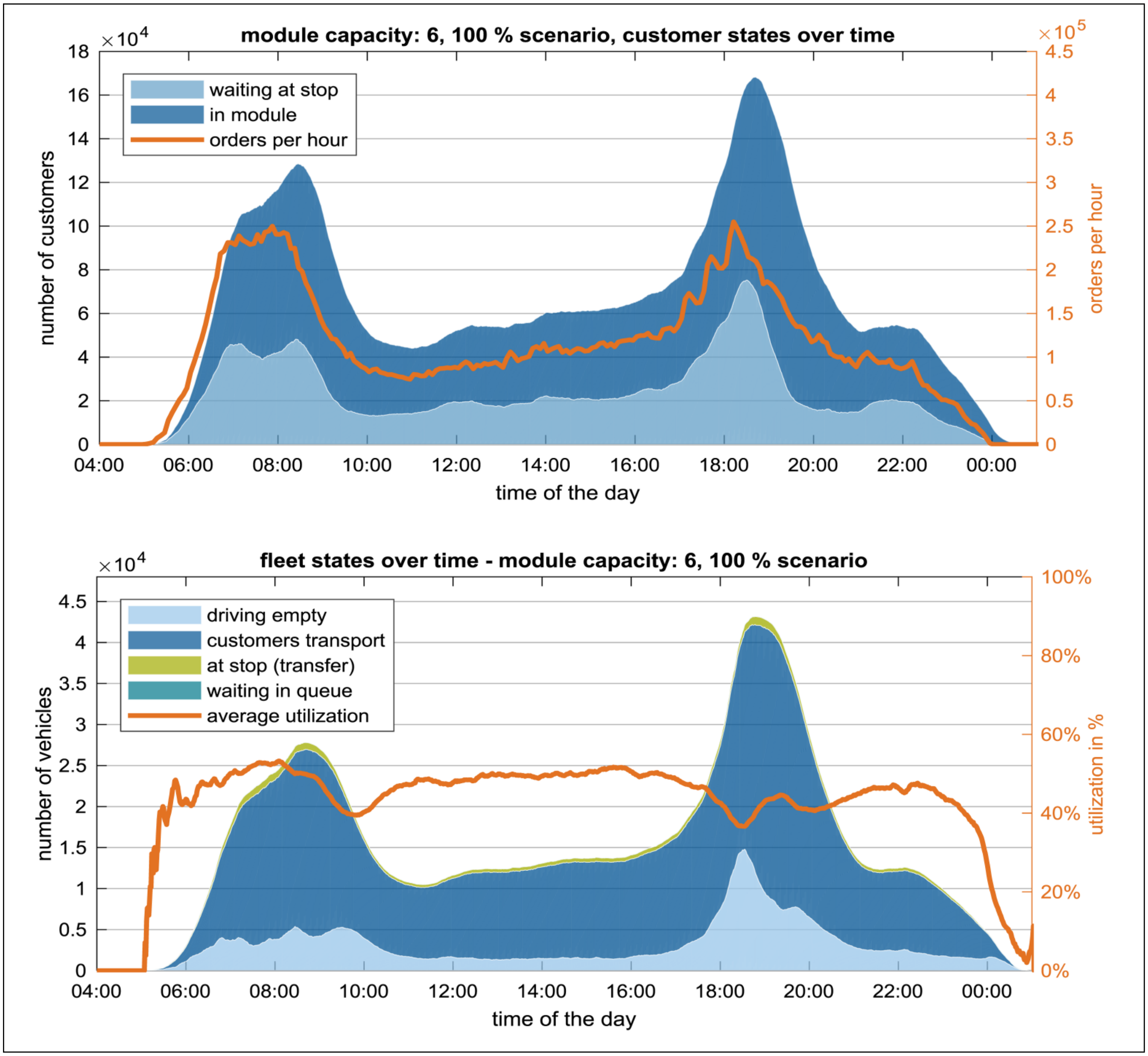

Figure 9. System analysis: vehicle states and customers over time.

all public transport journeys over several days. We filtered the data for only valid bus trips and extracted a weekday sample. Consecutive bus trips were combined into a single journey. Operation hours are from 5:00 to 12:00 a.m. This preprocessing step led to a list of 2.3 million demand events.

Traffic

The utilized routing engine provides travel times based on free-floating traffic. To consider real road conditions more accurately, a time-dependent traffic factor was introduced. This factor adopts the timing of routing results and is based on spatial-temporal fleet activity. Temporally, a speed factor distribution regarding the time of day was created using real traffic data. With a large fleet of simulated vehicles and the transport tasks representing real traffic demand, it is assumed that the known vehicles can be used as a good representation of the overall traffic. Assessing the vehicle's position and driving direction using a map grid, a speed factor for each position update event is determined by the time-based distribution. The traffic model was validated using the original trips' data with the average simulated speed being 4.6% slower than the original, and a standard deviation of 38.5%. Thus, the average travel times can be compared; however, due to the high standard deviation, single values can differ significantly.

Table 1. Performance Comparison

	Bus system			DRT system
	Diesel		Electric	
Fleet size		2,413		max. 43,165; avg. 16,073
Total seat capacity[a] in 1,000 persons		241		max. 259; avg. 96
Fleet distance per day in 1,000 km		547		5,393
Average utilization		18 %[a,b]		44%[c]
Fleet energy consumption per day in MWh	2,260[d]		985[e]	911[f]
Average trip time diff to bus		n/a		3.32 min (19.3%)
Average trip distance diff to bus		n/a		1.17 km (16.9%)

[a]estimated average capacity of 100 persons per bus (mix of single/double decker).
[b]average over distance.
[c]average over time.
[d]$E_{Consumption}$: 4.1 kWh/km (*21*).
[e]$E_{Consumption}$:1.8 kWh/km (*21*).
[f]$E_{Consumption}$: 0.169 kWh/km (22).

Vehicle Fleet

The chosen vehicle concept is a fully automated six-seater module with an electric powertrain. A variation of different seat capacities in a calibration phase showed that this module size is a good trade-off between operator- and customer-related needs. It benefits from a high utilization rate while providing a desirable quality of service.

System Behavior and Performance Analysis

Based on the described scenario, we evaluated the DRT system from a customer and operator point of view (Figure 9). The shift between the waiting customers and order-demand curve indicates that most customers are being picked up within a limited time frame. The mean customer waiting time is 12.1 min with a standard deviation of 10.9. In total, 0.07% of all trips are denied. In a comparison of the morning and evening peaks, a larger number of customers must wait during the evening peak. The diagram shows that at peak times, 170,000 customers are simultaneously active in the system.

By evaluating the fleet behavior, it is evident that the quantity of vehicles follows the demand. At the same time, the system is able to achieve a nearly constant utilization over time, indicating a limitation due to the dispatching. Many vehicles enter and leave the system at the beginning and at the end of peak times, indicated by the empty driving modules, either driving to the first customer or returning to the depot. This affects utilization, which decreases with a higher number of empty vehicles and increases again once they leave the system. With 43,165 modules active, the evening peak defines the required fleet size.

Discussion

With the demand being based on real bus trips, it is possible to compare the system performance between the existing bus and proposed DRT system. In 2013, LTA claimed the average daily ridership for buses to be 3.6 million passenger trips (*20*). Since this study simulated a demand of 2.3 million trips, the authors prorated the published data by a factor of 64%.

Table 1 summarizes the main results. In comparison with the bus system, the DRT system requires many more vehicles. The total seat capacity is just slightly higher (259,000 vs. 241,000), which is only required for a short period of time (peak demand), while, on average, a seat capacity of 96,000 is sufficient. With around 18 times more vehicles, the total driven distance increases as well and adds up to 5.4 million km per day, which is around 10 times more than the bus fleet. Analyzing the energy consumption, the DRT system beats the current system, even when replacing the entire bus fleet with electric buses.

Regarding utilization, smaller vehicles share the demand better than buses, and the average achieved utilization, at 44%, is more than twice as high. The system maintains a constant utilization by adding and removing vehicles to and from the fleet. Comparing the trip distance and duration, one can see that the DRT system is not able to beat the current bus system, and each trip is, on average, 19% longer than the original bus trip, while requiring 17% more time as well. This can be explained by detours caused by other passengers. Due to the large network of bus lines in Singapore, a customer is most likely to choose bus routes with a fast and direct connection. 76% of all bus journeys have no transfer to other buses; 21% have one transfer; and 3% have two or more transfers. Since a bus journey consists on average of 1.25 trips, a DRT system without transfers reduces the number of trips by 25%.

Conclusion

This paper presents a simulation model for a DRT system operated by automated modules on a city scale. The primary objective is to support decision-making in the early planning stage. Its operation is designed as a stop-to-stop service on flexible routes. It starts with a customer requesting a transportation task at a stop. The chosen stop is responsible for assigning the given order to a matching vehicle. The dispatch principle forms an auction mechanism realized by a contract net protocol. First, the solution space of transportation options is reduced by heuristically preselecting a subset of modules. Criteria are related to distances, planned activities, and vehicle states. The stop sends a call for a proposal message to the candidates and requests a cost estimation to fulfill the offered job. Each module calculates the effort. It is then the stop's responsibility to select the most suitable vehicle for the given transportation request.

The simulation approach itself is based on a discrete event-based multi-agent simulation. Agents are intelligent entities living independently in a shared environment. They solve the given dial-a-ride problem in competition.

A simulation study evaluated the potential to use a DRT system as a replacement for an existing bus system. The authors investigated a citywide operation with a total of 2.3 million requests per day. The results show a need for 43,165 six-seater modules. Due to its demand-driven design, the modules leave the system once no longer required and achieve constant utilization over time. Inactive vehicles are available for secondary use. On average, 16,073 modules are active.

The developed system is able to reduce total energy consumption, but service comfort cannot be improved at this stage of development.

The static bus route design outperforms the dynamic one, since passengers in a module may have different destinations, or a module may have to pick up new customers at additional stops.

Further research is required in order to create a superior system that is attractive to customers as well as operators. One idea is to improve the ridesharing potential by aggregating trip requests within a given time frame or by combining passengers with the same destination. Customer waiting time could be reduced by allowing parking along the street or at stop locations. To investigate the effects of additional congestion introduced by the DRT fleet, the model can be coupled with a traffic simulation. To examine different passenger responses, an extended order behavior model could be included.

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Author Contributions

The authors confirm contributing to the paper as follows: study conception and design: Benedikt Jäger, Carsten Brickwedde; data collection: Benedikt Jäger, Carsten Brickwedde; analysis and interpretation of results: Benedikt Jäger, Carsten Brickwedde; draft manuscript preparation: Benedikt Jäger. All authors reviewed the results and approved the final version of the manuscript.

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