Simulation in Produktion
und Logistik 2021
Jörg Franke & Peter Schuderer (Hrsg.)
Cuvillier Verlag, Göttingen 2021

A modular, discrete-event simulation framework for modelling free ranging transportation vehicles in intralogistics

Ein modulares, ereignisdiskretes Simulationsframework zur Modellierung freinavigierender Transportfahrzeuge in der Intralogistik

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Abstract: This publication presents a novel simulation framework for modelling fleets of autonomous, free ranging transportation vehicles in intralogistics. It aims at overcoming current shortcomings of popular, commercial DES tools in connection with free ranging vehicles like possibilities to apply sophisticated routing strategies. It is driven by the needs of fast simulation times and an accurate reproduction of the vehicles' free ranging behaviour. So, the presented framework combines elements from manufacturing and robotics simulation tools. In general, it can be applied for planning and assessing intralogistics systems to be equipped with Autonomous Intelligent Vehicles and e.g. to evaluate the performance of different fleet control strategies—especially in connection with large vehicle fleet sizes. This publication presents the general, structure of the discrete-event framework, discusses specific advantages and disadvantages and shows a possible connection to a reinforcement learning approach as an example.

1 Introduction

Opposed to traditional guided vehicles, free ranging transportation vehicles in intralogistics do not rely on predefined, static roadmaps and hence, can use the entire available space for moving. These vehicles are able to localize themselves in a familiar environment with the help of sensors like laser scanners, for example due to "natural navigation" (De Ryck et al. 2020). Furthermore, modern vehicles are usually autonomous, which means they can make decisions (e.g. which route to take towards a destination) individually (Fottner et al. 2021). As distinct from guided vehicles (AGV), within this contribution we call these autonomous, free ranging transportation vehicles AIV, Autonomous Intelligent Vehicles.

Though transportation systems based on AGV are still industry standard, we expect fleets of AIV to be increasingly used in the future. As AIV are able to travel on the direct link the transportation distances and consequently the transportation times are supposed to be shorter in general (Xin et al. 2015). Furthermore, AIV can deviate from planned routes more easily in order to avoid apparent conflicts and circumnavigate obstacles, which results in more flexible transportation systems. However, the higher degree of freedom of each vehicle leads to more complex systems from a control perspective; especially for large fleets (Güller et al. 2018).

Generally speaking, simulation is a very important tool with regard to material flow analyses of vehicle-based transportation systems. Analytical approaches can hardly display numerous interdependencies and high system dynamics, such as vehicle kinematics, vehicle congestion etc. However, a low simulation runtime and simulating large fleets of autonomous, free ranging vehicles in the intralogistics context, while ensuring a "proper" level of detail are contradicting objectives—hardly surprising there is a lack of commercial tools allowing simulation of AIV in accordance to our demands. So, in this publication, we present a discrete-event framework that

- is capable of simulating large AIV fleets,
- is able to display free ranging behaviour (especially in connection with conflict and collision avoidance) in a "sufficiently" level of detail, and
- shows "satisfactory" simulation execution times.

The publication is structured as follows: Section 2 briefly describes the general structure of routing algorithms for free ranging vehicles. Section 3 gives a quick overview of existing simulation tools. This includes software from the fields of manufacturing and robotics. Section 4 describes the general idea and structure of our AIV-simulation framework. Section 4 also exemplarily shows how a reinforcement learning approach applied for routing can be implemented. Section 5 discusses general advantages and disadvantages and possible fields of application.

2 Routing of free ranging vehicles

The routing of AIV is a challenging task—especially with increasing fleet sizes and its corresponding system dynamics. As AIV routing was also our motivation for applying simulation techniques and lead us to develop a suitable simulator, a short introduction and overview follows:

Regarding the routing of vehicles, many approaches and surveys present a similar dichotomy (see e.g. Taghaboni-Dutta 1995, Duchoň et al. 2014, Gasparetto 2015, De Ryck et al. 2020): A first subtask, which we name *route planning*, is responsible for finding a general, feasible route (global route) towards a destination taking only static layout information into account. Here, most of the approaches apply shortest-route-algorithms. A second subtask, which we name *motion coordination*, adjusts the vehicle´s movements during the execution of the global route with regard to mechanical limitations, e.g. in order to avoid and circumnavigate emergent obstacles. The specific routing strategy has significant impact on the number of routing conflicts, possible congestion in the system and hence, the overall transportation system performance.

3 State of the art in simulation of free ranging vehicles

In order to plan, design and analyse transportation systems based on AIV fleets, from a material flow perspective an appropriate simulation tool needs to fulfil the following requirements:

- A modularized structure with standardized interfaces that allows the implementation of different routing approaches that approximate the routing (route planning and motion coordination, see section 2) of free ranging vehicles.
- The ability to model different transportation patterns, stress scenarios, etc.
- An evaluation that calculates the most important logistics indicators, such as throughput, travel times, due dates or an overall density map, with regard to congestion in the system.
- The capability to perform extensive simulation studies for large fleet sizes (> 50 vehicles), i.e. “empirical investigation of a model’s behaviour by a set of simulation runs with a systematic variation” (VDI standard 3633-1).
- A visualization of simulation runs.
- Open source availability.

In general, there are two fields, where the simulation of AIV is important: “manufacturing” and “robotics” (Demesure et al. 2016). Similarly, the VDI standard 2710-3 distinguishes the two simulation types “logistical, dynamic simulation” and “emulation”. Also, ter Mors (2010) discusses a similar subdivision into the problems of “multi-agent route planning” and “robot motion planning”.

The following subsections describe both fields briefly and shows that each addresses aspects which are not considered by the other (Demesure et al. 2016). There are different points of interest and hence different characteristics of the corresponding simulation tools with respect to issues that can be modelled and analysed.

3.1 Manufacturing simulation tools

Compared to the robotics perspective (see subsection 3.2), typical manufacturing simulators have a focus on the higher-order manufacturing/production/warehouse system. Consequently, the transportation system is usually seen as a part of a greater system and therefore displayed with a significant degree of abstraction. With regard to vehicle-based transportation systems in general, the following describes typical tasks for the application of simulation tools with a focus on manufacturing:

- An evaluation of the general transportation system design with regard to specific intralogistics indicators such as overall throughput or vehicle utilization, or a sensitivity analysis of specific vehicle parameters, e.g. the fleet size or the handling time (see e.g. Um et al. 2009, Ben-Salem et al. 2017).
- The influence and effect of specific vehicle control strategies, such as the vehicle dispatching or the route planning (see e.g. Caridá et al. 2015, Fanti et al. 2018).
- The visualization of a production system/warehouse (see e.g. Rohrer 2000).

Popular simulation tools with a manufacturing focus can be found in Law (2013). Such tools usually provide a variety of predefined components and performance indicators concerning (intra)logistics and manufacturing systems in general. Depending on the model’s complexity, these tools can be very fast (simulation time compared to real time), which allows simulation studies with multiple thousand runs.

Regarding free ranging vehicles, it is possible to model the routing behaviour in a more or less abstract manner, depending on the exact focus of the specific tool. This ranges from workarounds with predefined grid-based roadmaps to vehicles that are capable of moving roughly on the air-line between two defined points.

3.2 Mobile robotics simulation tools

Opposed to the high-level abstraction of the manufacturing field (see subsection 3.1), simulation tools from the robotics field have a very detailed perspective on the behaviour of each individual vehicle, or rather robot, in its environment. In general, this simulation domain supports the development, design and testing of mechanical components and the corresponding control systems. In order to be close to the real world, these tools emulate realistic sensor feedback in detail, or include realistic physics engines. Furthermore, typical tools are capable of incorporating real world control algorithms, which results in a close to real-world behaviour of simulated robots. This allows users to focus on a specific aspect of a mobile robot while the other parts are accurately displayed by default (Žlajpah 2008). For example, simulation tools can be used for the following tasks:

- The in-depth development and testing of the robot motion control with regard to specific hardware setups (see e.g. Al Mamun et al. 2018).
- The examination of the exact behaviour of a robot in challenging environments, e.g. with humans (see e.g. Liu et al. 2017) or in an uneven terrain (see e.g. Wang et al. 2017).
- The evaluation of localization and mapping approaches (see e.g. Miah et al. 2018).
- The exact visualization of the robot behaviour (Žlajpah 2008).

All in all, there are multiple tools with different individual key aspects. A survey regarding open source simulation software can be found in Torres-Torriti et al. (2016). Since the tools accurately simulate the real world and the behaviour of (in most of the cases single) robots, it is hardly possible to execute a simulation much faster than real time, due to a high calculation effort on the one hand and due to the incorporation of a control that was not designed for that on the other hand. Hence, an adequate simulation study of AIV fleets against the background of intralogistics questions is rather unpractical.

4 Simulation framework

This section gives a motivation for the design of a new simulation framework (4.1.), describes the developed framework in detail (4.2) and shows an example application (4.3). In general, the following subsections show the framework rather from a user perspective instead of a software engineering perspective.

4.1 Motivation

In order to evaluate fleets of free ranging transportation vehicles in the intralogistics context with special focus on different routing strategies, we could not find a suitable simulation tool on the market. On the one hand, there are well established tools with focus on manufacturing systems (see subsection 3.1). Unfortunately, they either do not provide the opportunity to adequately implement AIV and their complex free ranging routing algorithms at all or it is very time consuming to implement them into the corresponding simulation tools' infrastructure (Schneider et al. 2019). On the other hand, typical tools from the field of robotics (see subsection 3.2) with their in-depth focus on an exact vehicle behaviour and environment are not designed for conducting extensive simulation studies of large fleet sizes and automatically deriving and analysing logistics performance indicators.

4.2 Structure and modules

Our application relies on the python discrete-event simulation framework *simpy* (Matloff 2009). In general, the discrete-event paradigm is beneficial for a fast execution of the simulation (Law 2013). Python was chosen since it is a widely used language in science and industry, has an active community support and contains useful packages and frameworks, e.g. for data analytics or machine learning (Tambad et al. 2020). This allows to combine the simulation framework for example with reinforcement learning approaches, as will be shown in subsection 4.3.

Figure 1 displays the general structure of our framework. In an *experiment environment* the user can define all input parameters of a scenario, such as the layout, vehicle characteristics, etc. Furthermore, the user can define a specific experiment, which is defined by the parameters to investigate in a sensitivity analysis, e.g. the fleet size. A *design of experiment* module automatically creates the corresponding input parameter files for all necessary runs and finally starts the simulation runs.

The *core* of the simulation is responsible for keeping all events synchronized (especially the vehicle movements), updating the system status, generating new transportation tasks and creating the necessary log files for a subsequent analysis.

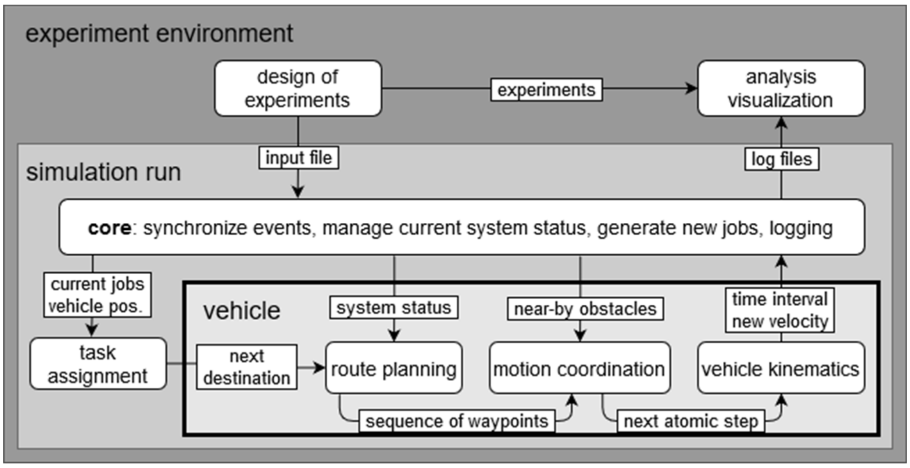

Figure 1: *general structure and components of the simulation framework*

The *task assignment* module is responsible for assigning transportation tasks to specific vehicles or vice versa assigning vehicles to specific tasks. The module's input are the current system status regarding open transportation tasks and vehicle positions in the layout. It is possible to apply very basic dispatching rules ("nearest job first") or even a sophisticated vehicle scheduling algorithm with a high look-ahead period. All in all, this module permanently determines the next destination for each vehicle.

Each vehicle individually executes the following three modules (route planning, motion coordination and kinematics), which represent a vehicle´s autonomous routing behaviour. Based on the current destination as defined by the task assignment module, the *route planning* module determines a global route (see section 2). Different strategies can be applied in this module, like a shortest distance route (if a roadmap exists) or standard approaches for free ranging vehicles (e.g. rapidly exploring random trees). The route planning approach can theoretically make use of the entire global information (especially current position and destination of the other vehicles) or can just rely on local information or the vehicles individual experience (past travel times). It results in a sequence of (way)points that lead a vehicle to its destination.

The *motion coordination* module determines atomic steps between the waypoints taking a vehicle´s local environment into consideration (see section 2). If there are dynamic obstacles near-by, such as other vehicles, the motion coordination of a vehicle will adapt the next steps in order to avoid a collision and resolve the routing conflict. Hence, physical collisions are prohibited. An example for a typical motion coordination approach is a so-called potential field method that calculates the next atomic direction with regard to attractive and repulsive forces in the local environment. The result of this module is an atomic step that does not violate the safety distance to any static or dynamic obstacle nearby.

The *vehicle kinematics* module transfers an atomic step as determined by the motion coordination into a corresponding atomic time interval taking the current vehicle velocity, possible acceleration/necessary deceleration, and the past and new direction of a step into account. This time interval and the coordinates of the next step are the main feedback to the simulation core, which keeps track of the vehicles' positions and movements. After the vehicle was delayed accordingly, the next atomic step can be calculated based on the new system status. For each vehicle, as long as there is a destination (and therefore next waypoints) defined, the simulation infinitely executes the loop of motion coordination, vehicle kinematics, and corresponding delays.

With regard to the design of experiments, the simulation saves relevant log files (global routes, atomic vehicle positions and steps, routing conflicts and congestion, job time stamps, etc.) for an *analysis*, or a subsequent *visualization* of a run. Furthermore, diagrams with predefined structure are created and stored automatically.

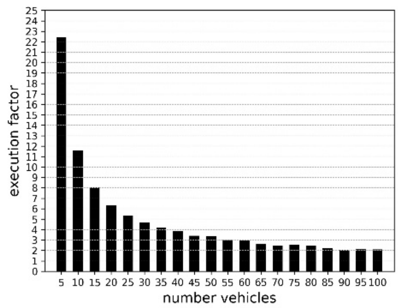

Figure 2: *Average simulation execution factor (simulated time divided by real time).*

In order to give a rough idea about the reachable simulation speed, Figure 2 displays the average simulation execution factor (how much faster is the simulation runtime compared to real time) with regard to the simulated fleet size as computed on an intel core i5, 2.5GHz, 2 cores. Large fleets with about 50 vehicles are simulated approximately 3 times faster than the reality, fleets with about 100 vehicles lead to an execution factor of about 2. However, the exact speed for a specific use case is also dependent on the layout and various simulation parameters.

4.3 Example: route planning using reinforcement learning

In order to give a deeper insight into the simulation framework, this example demonstrates its application and some core procedures. Figure 3 displays a layout (grey background) with two locations (crosses) and 6 obstacles (dark grey boxes). From a taxicab geometry perspective, there are 16 possible routes between both locations, whereas 10 routes can be considered as candidate routes (without detour). The best route to take in a specific situation depends on the current system status, i.e. the position and routes of other vehicles. It is possible to apply various algorithms for the route planning, i.e. for the identification of possible routes and the choice of a best route exemplarily. The following describes a reinforcement learning approach.

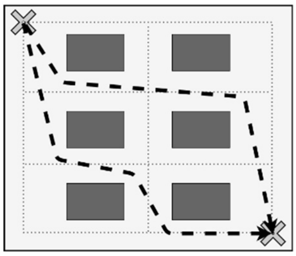

Figure 3: *Example layout with two defined locations, an underlying grid roadmap and two alternative candidate routes as they are executed by AIV.*

Figure 4 displays the elements of the reinforcement learning approach as included in the route planning module (see Figure 1). Before the simulation starts, a determination of possible global routes between different locations has to be done, e.g. finding all possible paths between two locations. With the information of the next destination (result of task assignment module), an artificial neural network (ANN) determines a specific route index (classification problem). Afterwards, the resulting index can be exactly matched to a specific predefined route and therefore a corresponding sequence of waypoints, which is the result of the route planning.

In the simulation, the vehicle executes the sequence of waypoints, while avoiding apparent routing conflicts with other vehicles (motion coordination). After reaching the final destination, the exact transportation time (reward) can be determined retroactively. A batch containing the particular basis for the decisions (observations), the choices for a route (actions) and the corresponding transportation times (rewards) trains the ANN.

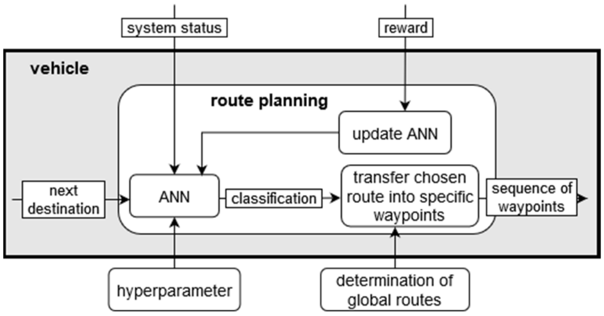

Figure 4: *Example of a reinforcement learning approach as route planning.*

Generally speaking, it is possible to use an ANN to select a vehicle´s route without taking the current system status (position and destination of other vehicles) into consideration. This leads to a relatively simple problem, where vehicles individually learn which routes between different points are beneficial in general. Over time, opposing traffic flows avoid themselves, resulting in one-way directions in bottlenecks. Opposed to that, with the ANN taking the current system status into consideration, a more complex problem arises. Here, each vehicle learns over time which route is beneficial in specific situations, in order to reach the destination quickly while avoiding routing conflicts with other vehicles.

5 Discussion

We created a simulation framework with focus on modelling the routing procedure of a fleet of free ranging transportation vehicles in intralogistics. The framework allows to implement different vehicle (control) strategies for the modules of "task assignment", "route planning", "motion coordination" and "vehicle kinematics". The strategies and parameters can be approximated in order to realize an individual compromise between an accurate AIV behaviour and fast simulation runtimes. The advantages and disadvantages of the framework can be derived from this compromise.

The tool is fast enough to perform extensive simulation studies even with larger fleet sizes. It is modular, so different routing or task assignment strategies can be interchanged and evaluated quickly. Therefore, it can be used to assess general control strategies in preliminary studies. The tool automatically designs, executes and analyses necessary simulations with regard to predefined experiment parameters. It allows an "out-of-the-box" implementation of general routing strategies for AIV and evaluation with regard to logistics indicators.

Since there is only an approximation of the free ranging behaviour, the simulation tool however is not suitable for the in-depth analysis of a real world control, or the examination of the vehicle behaviour in a realistic environment. Effects like inter-vehicle communication, a physics engine, realistic vehicle sensing are not included.

The validity of a simulation based on the described framework is dependent on the exact control strategies and parameters applied, e.g. in the modules of route planning, motion coordination and vehicle kinematics. It needs to be determined individually with regard to the chosen algorithms/parameters for these modules and the corresponding real world system.

6 Conclusion

This publication presented a simulation framework for the simulation of an intralogistics transportation system based on free ranging and autonomous vehicles. The framework aims at finding a compromise between a high simulation speed and the depiction of free ranging vehicle behaviour. The general idea and modular structure of the framework was presented as well as a combination with a reinforcement learning approach as an example.

In the future we plan to further improve the framework with regard to vehicle kinematics and implement standard algorithms for the route planning, motion coordination and task assignment. Also, we plan to apply simulations based on the presented framework in future research projects.

Acknowledgement

The work was carried out as a part of the IGF research project 20516 BR "SVAT" (Schwarmverhalten autonomer Transportsysteme) and supported by "Forschungsgemeinschaft Intralogistik/Fördertechnik und Logistiksysteme (IFL) e.V.".

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