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# Modeling Autonomously Controlled Automobile Terminal Processes

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**Purpose:** Automobile terminals play an essential role in automotive supply chains. Due to short planning cycles and volatile planning information, the yard assignment determines terminals performance. Existing planning approaches are not able to cope with these dynamics. This contribution proposes a novel bio-analogue autonomous control method to face these dynamics, its effects and to improve the terminals performance.

**Methodology:** Causes of internal and external terminals dynamics will be discussed and an autonomous control method will be derived. A generic parameterizable automobile terminal model and its implementation to a discrete event simulation will be introduced in this paper. This simulation is used to compare the new approach to classical yard assignment.

**Findings:** This paper contributes to the theoretical understanding of causes and effects of dynamics in the context of automobile terminals. It will show that autonomous control outperforms classical approaches under highly dynamic conditions.

**Originality:** The generic modelling approach is a novel description of automobile terminals. It allows investigations of a broad spectrum of use cases. Moreover, the bio-analogue autonomous control for automobile terminals is an innovative approach.

**Keywords:** Automobile Logistics, Port Terminal, Autonomous Control, Discrete Event Simulation

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## 1 Introduction

During the recent years, the shipment volume of finished cars increased constantly, due to an emerging global interconnection between production and distribution networks. In this context, automobile terminals are central elements in international automotive supply chains. Automobile terminals allow the transshipment from the production plant to the target markets. Besides handling of finished cars from different transport modes (e.g., ship or truck), these terminals usually offer a broad spectrum of additional technical services in order to meet customers' demands in the port of destination. In general, the main tasks of automobile terminals can be defined as handling, technical treatment and storage of finished vehicles (Mattfeld, 2006; Böse and Piotrowski, 2009). All related processes are triggered directly by the car manufacturers (OEM). Accordingly, automobile terminals can be interpreted as a classical decoupling point in the automotive supply chain, which allows to react flexibly to demand fluctuations (Dias, Calado and Mendonça, 2010). Hence, planning of processes automobile terminals is faced with forecast-driven and customer-order driven processes at the same time. This strongly affects the yard master planning, which aims at minimizing the distance between the point of car entrance, storage area and its exit point (Görge and Freitag, 2019). Classical master planning approaches solve this task by assigning predefined parking areas to the different vehicle types (e.g. sorted by manufacturer, model and destination). This leads to good planning results for situations with high forecast quality and less dynamics. However, due to its long term orientation, this type of yard

master planning is prone to forecast deviations, volatile parameter variations and unforeseen events, which may affect the terminals performance negatively (Cordeau et al., 2011; Mattfeld and Orth, 2006).

Autonomous control of logistics processes address these shortcomings by transferring decision making capabilities from a centralized planning instance to the logistics object itself. Due to interactions and decision making of intelligent logistics objects, autonomous control aims at creating self-organizing systems behavior, which increases the systems performance (Windt and Hülsmann, 2007). This self-organization can be seen as emergent behavior of a complex dynamic system, which is not a characteristic of the systems elements but of the total system (Vaario and Ueda, 1998). For production logistics, different autonomous control strategies showed already their operational potential. In the context of automobile terminals, first implementations indicated promising results concerning the assignment of cars in import processes to technical service stations (Böse and Piotrowski, 2009). However, comprehensive autonomous control strategies covering all inbound and outbound material flows of an automobile terminal are still missing. Thus, this paper will focus a broader use case. It will derive an autonomous control strategy, which allows the integration all flows of cars (import, export and inter terminal) at an automobile terminal. In order to analyze the performance of the autonomous control strategy, this paper will present a generic modeling approach for investigating a broad range of related scenarios. Furthermore, it will introduce a discrete event simulation model implementation for analyzing these scenarios. This simulation model will be used to investigate the performance of the derived autonomous control method compared to a classical yard master plan.

## 2 Autonomous Control of Automobile Terminals

### 2.1 Terminal Planning

Material flows in automobile terminals can be characterized as a sequence of several generic sub processes (e.g. loading or storage operations). Basically, every process starts with unloading operations from different transport carriers (truck, rail, ship) followed by the storage of the vehicle. Subsequently, cars are loaded to outbound transport carriers or receive one or more technical services. Automobile terminals offer a broad spectrum of technical services with highly varying process times (Hoff-Hoffmeyer-Zlotnik et al., 2017). Figure 1 depicts this physical material flow of vehicles at an automobile terminal. Furthermore, it shows the related planning tasks in respect to their temporal occurrence (planning horizon). The overall objective of all planning tasks is the efficient operation of all physical vehicle movements from the source (i.e. unloading point at the terminal) to the sink (i.e. loading point) (Özkan, Nas and Güler, 2016). On a strategic level, planning focuses on long term decisions like the planning of infrastructure (e.g. additional berth or yard extensions). Forecasting of expected vehicle volumes and related long-term planning of resources belong to this strategic time horizon as well. Based on these forecasts, a long term orientated area master planning derives required parking areas (Mattfeld, 2006). A result of this planning step is a rough assignment of estimated vehicle volumes to parking areas. This first assignment is the starting point for the tasks on the tactical planning horizon. In this planning phase, forecasted vehicle volumes are used to plan berths and the utilizations of berths (Dias, Calado and Mendonça, 2010). Usually, forecasts be-

come more precise and get a higher level of detail with more specific information (e.g. model-destination split or volume related model-split). The results of the strategic planning is used in the tactical planning to generate and adjust the yard plan. The yard plan comprises the assignment of vehicle volumes to specific areas of the yard. In order to generate short routes between the loading and unloading locations, the yard planning often includes the localization of loading and unloading operations (berth allocation planning, storage space partitioning and storage area design) (Mattfeld, 2006; Mattfeld and Orth, 2006). The personnel requirement can be derived with the results of localization and vehicle assignment. In general, the operational planning is characterized by increasing level of relevant information (e.g. ETA of ships or the assignment of cars to ships). On this operational planning level, the results of tactical planning are refined in predefined turns or with a rolling time horizon (Mattfeld and Kopfer, 2003). This approach allows to react to changes and external disturbances (e.g. delay of ships or changes in ships transport quantities).

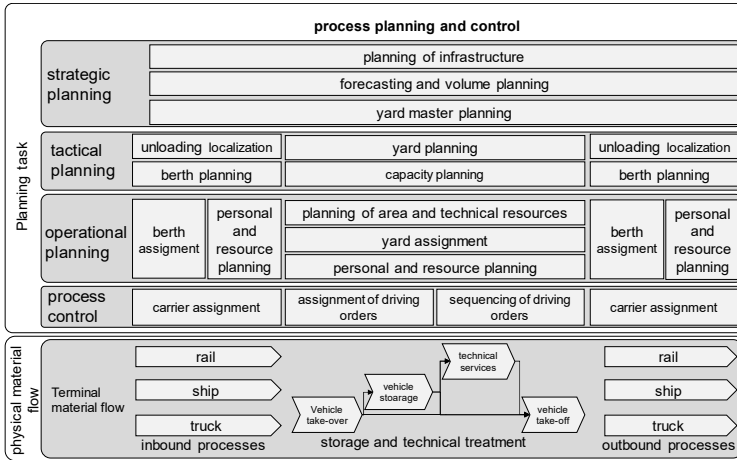


Figure 1: terminals planning task – based on (Görge and Freitag, 2019)

These plan adjustments may lead to changes of routes length between inbound locations, storage areas and outbound locations and affect the overall terminals productivity and the personal requirements. The process control focuses on the execution of particular driving orders resulting from the previous planning tasks. It assigns driving orders to workers and monitors the progress of order processing

Yard planning plays a key role in the described, cascaded planning process. It mainly determines driving distances between cars' arrival and departure points and the related process productivity (i.e. cars per hour per worker). Incoming vehicles are sorted and assigned to parking lots according to the yard master plan. At the arrival of a vehicle, usually the information about its outgoing transport carrier is not available. Later, the customer (e.g. OEM) sends advices for particular cars, assigning them, for example, to a specific ship. Dias et al. (2010) describe this characteristic as parallel push

and pull processes occurring at the same time at an automobile terminal (Dias, Calado and Mendonça, 2010). These parallel push and pull processes allow terminals to react quickly to changing demands in the supply chain. However, this also leads to complex internal dynamics in the terminals processes and short planning time horizons. Classical yard planning addresses the orders' neutral (forecast-driven) aspect. Volumes of vehicles are assigned to specific parking areas of the terminal based on forecasts. After customer orders are available, the operational planning (e.g., berth planning) aims at increasing the terminals productivity by reducing distances between storage area of the cars and the outgoing transport carrier (e.g., by assigning ships to quay positions). Figure 2 depicts both push and pull processes of automobile terminals and relates them to the planning tasks. In this context, terminals offer a higher degree of flexibility to the entire supply chain at expense of an increasing complexity of the terminals' planning and its operative process execution. In this context, the yard planning is a key instrument to cope with forecasted vehicle volumes and to allocate it to parking areas.

Accordingly, it determines routes of vehicles from the source to the sink on the terminal. Due to the order-natural nature of the arrival process, the yard planning cannot react to near-term changes (e.g., increasing or decreasing vehicle volumes). An increasing degree of flexibility and dynamical adjustment of yard assignments may increase the terminals' performance (Görges and Freitag, 2019).

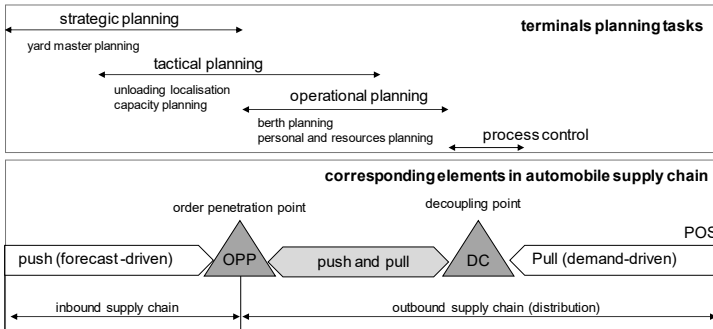


Figure 2: terminal planning in the context of automobile supply chains based on (Dias, Calado and Mendonça, 2010)

## 2.2 Concept of Autonomous Control

The concept of autonomous control offers a novel approach to cope with dynamics in logistic systems. It aims at transferring decision making capabilities from a centralized planning instance to the logistics object (e.g., goods or machines). By enabling decentralized decision making, autonomous control intends to create an emergent systems behavior which allows to deal with dynamics and increases the systems performance. Autonomous control is not limited to specific types of logistics systems. There are different approaches for production logistics (Toshniwal et al., 2011), for transport logistics (Rekersbrink, Makuschewitz and Scholz-Reiter, 2009) and for aspects of terminal logistics (Böse and Piotrowski, 2009), by implementing local decentralized decision making capabilities. Wind and Hülsmann (2007) introduced the term intelligent logistics object. Intelligent logistics objects cover both, physical real world objects (e.g., vehicles on a terminal) and immaterial objects like customer orders. By using modern

communication technologies, intelligent logistics objects are capable to exchange and collect information about relevant system states (Windt and Hülsmann, 2007). Existing autonomous control methods can be classified as local information methods and information discovery methods. Local information methods collect and process only local system information. They can be further classified as rational, bounded rational and combined decision strategies (Scholz-Reiter, Rekersbrink and Görge, 2010). Rational methods use performance measures like estimated throughput times, inventory or route distances for decision making. Bounded rational strategies try to adapt complex decision patterns from other systems. Often these strategies are inspired by biologic systems phenomena (e.g., foraging behavior of insects or bacteria). A combined strategy is based on bounded rational decision mechanism and adds rational aspects (e.g. for a better implementation of restrictions).

By contrast, information discovery methods receive relevant information from interactions with other logistics objects. In this context the requested information can be passed along several logistics objects. Usually these information request do not cover the entire system, but is directed to relevant local information. Existing information discovery methods are inspired by technical protocols for communication networks and transfer routing mechanisms from these protocols to autonomous decision making of logistics objects (Rekersbrink, Makuschewitz and Scholz-Reiter, 2009). Due to their complexity, information discovery methods are designed for specific logistics scenarios (vehicle routing or flexible flow shop scenarios) and cannot be easily transferred to other system types like automobile terminals. First approaches of integrating autonomous control to automobile terminals showed already promising results. Böse and Piotrowski (2009) present

a rational decision strategy for assigning cars to storage areas for technical treatment, which increases the handling performance (Böse and Piotrowski, 2009). However, this approach addresses specific sub processes of the import process and neglects cars arrival and departure points (e.g., berths). In order to design a comprehensive autonomous control strategy covering all processes of automobile terminals, a systematic approach is necessary. A procedure model for designing autonomous controlled automobile terminal processes is presented in (Görge and Freitag, 2019). In a first step a general target system has to be defined, which fits to the planning tasks and results described in section 2. In this respect, the total driving distance of vehicles (from the source to the sink) is a suitable and simple measure to analyze the methods performance. Subsequently, potential logistics objects for autonomous decision making have to be identified. In order to align the autonomous control strategy with terminals planning tasks, potential logistics objects should be the subjects of planning. In the case of automobile terminals, potential objects are: vehicles, vessels, trains and trucks. As a starting point this paper presents an autonomous control method for yard assignment of vehicles. This method considers status information of vessels, trains and trucks and allows autonomous decision making of vehicles choosing a parking row.

### **3 Generic Automobile Terminal Model**

#### **3.1 Structure of the Generic Scenario**

In order to derive and analyze methods for an autonomous yard assignment, this paper proposes a generic automobile terminal model. This generic scenario is organized on two hierarchical layers. On the top layer it

consists of  $n \times m$  adjustable parking areas ( $A_{11}$  to  $A_{nm}$ ). Cars arrive at the terminal via sources ( $I_1$  to  $I_k$ ) and leave the terminal system via sinks ( $O_1$  to  $O_j$ ). Figure 3 depicts the structure of this generic scenario. Sources and sinks may be modelled as incoming (or outgoing) trucks, trains or ships. All parking areas are surrounded by driveways allowing cars to get from a parking area to another (or to a sink).

The second layer describes the parking area and its properties. A parking area is defined by its height ( $h$ ), its width ( $w$ ), and the row width ( $r$ ). The number of parking rows ( $R_1$  to  $R_l$ ) results of these parameters. The orientation of rows is perpendicular to width dimension (see Figure 3). The row capacity is defined by  $h$  divided by the length of cars. The capacity of a parking area is defined by the sum of all rows' capacity.

This generic structure is the basis for the specific scenario investigated in this paper. In order to keep the scenario as simple as possible, a setting of 4x4 storage areas is used. The area width is  $w = 160m$ , the area height is  $h = 75m$  and the row width is  $r = 3m$  for each storage area. According to these parameters the terminal's capacity is 12720 cars with a standard length of 5m.

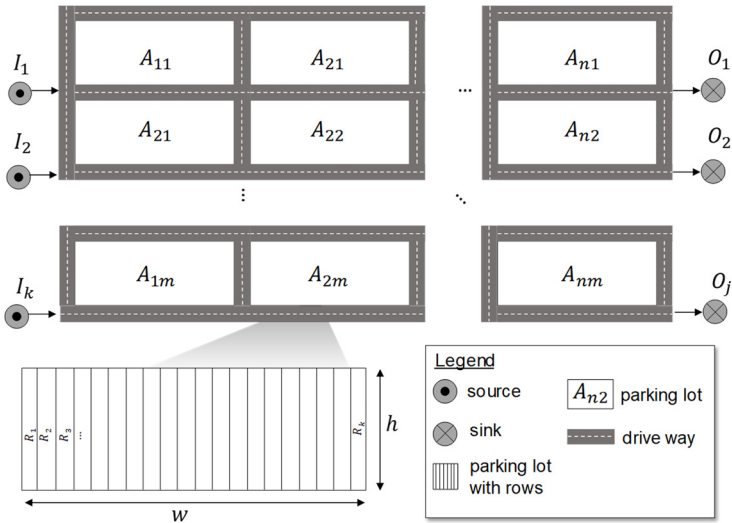


Figure 3: generic automobile terminal scenario

### 3.2 Modeling In- and Outbound Dynamics

The following section describes the general test settings used to parameterize inbound and outbound processes of cars. In this scenario two OEMs deliver their vehicles for export to the terminal by rail. Each OEM delivers two model types for two different destinations. A combination of OEM, model type and destination is defined as a category  $k$  of vehicles. The arriving volume of vehicles of a category  $k$  is defined by a sine function. This allows to model volatile seasonal demand fluctuations. Similar seasonal effects can be observed in arrival volumes of real automobile terminals. Equation (1) shows this function and its parameters.  $I^k(t)$  is the incoming

volume at day  $t$ . The mean arrival rate of vehicles is defined by  $\lambda^k$ . The amplitude of the sine function is defined by  $\mu^k$ . In order to avoid negative arrival volumes the amplitude has to be smaller than the mean arrival rate ( $\mu^k \leq \lambda^k$ ). Besides the mean arrival rate, the phase shift  $\varphi^k$  and the period  $T$  determine the dynamic characteristics of this arrival function.

$$I^k(t) = \lambda^k + \mu^k \cdot \sin\left(\frac{t}{T} + \varphi^k\right) \quad (1)$$

The following Table 1 shows the four categories of cars used in this scenario and the corresponding arrival parameters. It presents the values for  $\lambda^k$  for the particular implementation used in this paper.

Table 4: OEM's model and destination mix

OEMs	Model	Destina- tion	Mean arrival rate ( $\lambda$ ) [car/d]	Initial Inventory	Phase shift
OEM 1	M1	D1	100	1000	0%
OEM 1	M2	D2	75	1000	25%
OEM 2	M3	D1	100	1000	50%
OEM 2	M4	D2	75	1000	75%

In order to generate a realistic systems behavior, the terminals initial inventory has been set for every category to 1000 vehicles. The phase shift has been modeled in steps of 25% (related to the period of 365 days) for each category. The period  $T$  has be set to a quarter year. Figure 4 shows the sinusoidal inputs for all categories and the total input. The upper graph of Figure 4 depicts exemplarily the input volumes of OEM 1 model M1 and OEM 2 model M3.

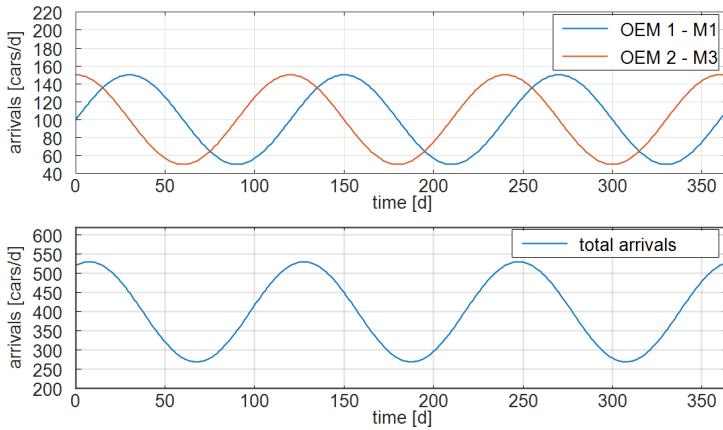


Figure 4: arrivals of OEM 1 & OEM2 (top); total arrivals (bottom)

Table 2: inventory times

	OEM 1 - M1	OEM 1 - M2	OEM 2 - M3	OEM 2 - M4
avg. inventory time [d]	10	20	10	20
variance [d]	2	2	2	2

The departure of vehicles is modelled in two different variants. The first variant uses simple constant inventory times modelled by adding a normal distributed delay to the arrival time of each vehicle. Accordingly, cars leave the terminal after a predefined time. Table 2 summarizes the underlying departure rates.

The second variant models the departure of cars in a more realistic way. In this variant ships sailing to destination D1 and D2 are generated as a time series with a normal distributed shipment volume per vessel.

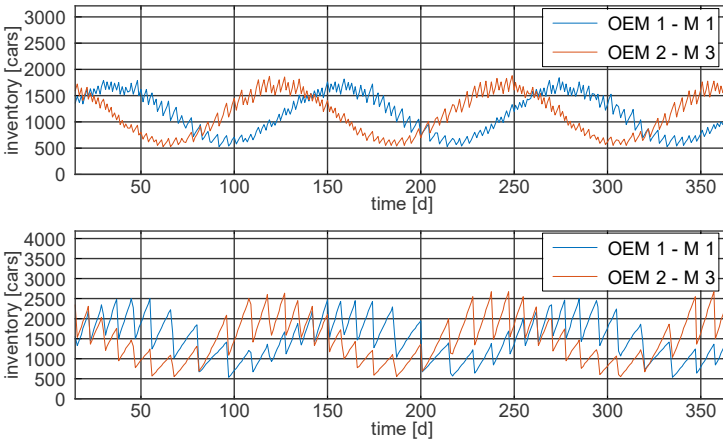


Figure 5: inventory over time: avg. 600 cars per ship (top); avg. 2000 cars per ship (bottom) for bulked departures

The ships arriving at the terminal have an average capacity based on a normal distribution. This leads to a bulked departure of cars over time. In this scenario, the average ships' capacity  $s$  will be varied from 500 to 2000 with a standard deviation of 10% of the mean value. Figure 5 shows the estimated inventory over time for different mean ships capacities. It shows that the mean ships parameter  $s$  has an impact on the dynamic of the inventory time series. Comparable inventory curves can be observed in real automobile terminals. This scenario comprises according to the sinusoidal inputs, the initial terminals inventory and the output rates (see Table 1 and Table

2) approximately 127.000 vehicles running through this scenario in 365 days.

In the 4x4 scaled scenario there are three sources and three sinks. The locations of sources and sinks will be addressed in detail in section 4.1 (Figure 6 summarizes their locations). The split of outgoing volumes of both OEMs is modelled as follows: At source 1 75% of OEM 1's volume arrive. At source 2 25% of OEM 1's and 25 % of OEM 2's volumes arrive and at source 3 75% of OEM 2's volume arrives. 75% of all ships sailing to destination 1 leave from sink 1, 20% from sink 2 and 5% from sink 3. For destination 2 75% leave from sink 3, 20% from sink 2 and 5% from sink 1.

## **4 Yard Assignment Methods**

### **4.1 Conventional Yard Assignment**

Based on these information a simple planning and assignment of cars to parking areas has been done. Figure 6 shows these assignments. The main concern of this assignment is to generate short routes between sources, storage areas and sinks. For example most cars of OEM 1 will arrive at source 1 and leave at all sinks. Thus, the assignments are close to source 1. Usually, different models from one OEM may be mixed when the terminals utilization is high. Thus, Figure 6 shows the primary assignment of cars and a secondary assignment in brackets. The secondary assignment can only be used if no free row of the primary assignment is available. These assignments are considered as results of a classical planning process in the following evaluation.

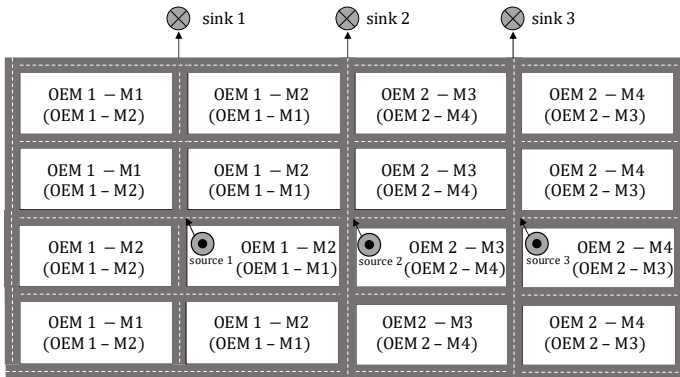


Figure 6: classical yard assignment

For the purpose of benchmarking a randomized assignment will also be used. In this case arriving cars are assigned to a randomly chosen row on the terminal. Only capacity restrictions of a row have to be met.

## 4.2 Phormone Based Autonomous Control Approach

The autonomous control method presented in this section allows cars to evaluate, to compare and to choose a parking row by a phormone based approach, which is inspired by ant's natural foraging behavior. As depicted earlier, bounded rational strategies like this offer the possibility to consider many different decision parameters. The method at hand can be seen as a combined method, using bounded rational aspects and rational measures. Phormone based approaches have shown their capability to react on dynamical changes and to stabilize the systems behavior under volatile conditions (Windt et al., 2010). Accordingly, this approach seems to be suitable

to the vehicles yard assignment at an automobile terminal. In general pheromone based methods imitate communication principles of social insects (i.e. ants). While searching for food, ants leave evaporating pheromone trails, marking possible routes to food sources. Other ants are attracted by these trails and follow it. Ants following a trail increase the pheromone concentration. The pheromone concentration decreases in time due to the natural evaporation process. By using this interplay between marking trails with pheromones on the one hand and natural evaporation process on the other hand, ants are able to find the shortest routes to food sources. Autonomous control methods using this principle leave relevant information in the system (e.g. throughput times) as an artificial pheromone. Subsequent objects are able to read this pheromone information to make a local decision on this basis and to follow the trail with the highest concentration. The evaporation process is often modeled as a moving average over a predefined set of objects running through the system (Armbruster et al., 2006). This paper proposes a similar approach for assigning vehicles to parking rows. Vehicles belonging to a category  $k$  calculate for every row  $i$  a pheromone value  $P_i^k$  and chose the row with the best  $P_i^k$  value. Equation (2) describes this pheromone value. The total number of vehicle categories is defined as  $K$ . In this context criteria for vehicle categories are OEM, model types and the shipment destination (see also Table 1).

$$P_i^k = \gamma_1 \left| \frac{RANG(W_i^k)}{F} - \frac{RANG(G_k)}{K} \right| + \gamma_2 \frac{d_i}{D^k} + \gamma_3 \left( 1 - \frac{v_i^k}{V^k} \right) + \gamma_4 \frac{\min(W_i^k)}{\max(W^k)} \quad (2)$$

The pheromone value  $P_i^k$  consists of four terms. Each term focuses on a different target value and can be weighted by a factor  $\gamma$ . Except from term 3 all remaining terms use the moving average concept to emulate the pheromone evaporation. All terms and the evaporation process will be described in the following. For each category  $k$  a moving average of the last  $\alpha$  vehicles

is used to determine two key parameters. The first parameters are the most frequented sources and sinks of the specific vehicle category. These parameters are the basis for deriving distance related measures like  $W_i^k$ . The  $W_i^k$  is defined as the distance between the most frequently used source, the storage area of the parking row  $i$  and the most frequently used sink. The second parameter is the moving average of the inventory time (days at the terminal)  $G_k$  of the vehicles belonging to category  $k$ .

The first term of the pheromone value equation (2) focuses on balancing the estimated distance  $W_i^k$  and the average inventory time  $G_k$  of a category  $k$ . The basic intention of this term is to rate rows with longer estimated distance better for categories with higher inventory time and vice versa. Therefore, this term calculates the ranking position of the estimated distance factor  $W_i^k$  divided by the amount of parking Areas  $F$  and relates it with the ranking of inventory day of remaining categories.

Most of terminal inbound and outbound processes operate in a FIFO mode. Thus, vehicles with same inventory times should stand closely together. The second term addresses the FIFO principle, by relating the inventory time of the latest vehicle in a storage area with the inventory time of the oldest vehicle of category  $k$ .

The third term addresses the split of vehicles on the terminal. An obvious constraint coming from the basic yard planning is to minimize the geographical dispersion of vehicles belonging to the same category. The number of different separated storage areas per category should be as less as possible. Therefore, this term relates the volume of vehicles of category  $v_i^k$  in the parking area of row  $i$  to the overall volume of vehicles  $V^k$  belonging to category  $k$ .

The fourth term focuses on the estimated distance for a vehicle stored on the parking area of row  $i$ . It tries to avoid an assignment, which lead to long driving distances. This term is defined as the ratio between the estimated distance  $W_i^k$  based on the moving average and the maximal possible distance for category  $k$  regarding all sources, storage areas and sinks.

The pheromone value for each row can be derived with equation (1). By contrast to natural process, vehicles choose the row with the lowest value of  $P_i^k$  as the highest concentration of pheromones.

## 5 Simulation Results

### 5.1 Impact of External Dynamics

An discrete event simulation model has been set up according to section 4. This model will be used to investigate the impact of external dynamics on the conventional yard assignment and the autonomous control method for the constant and the bulked departure variant. The parameter  $\mu^k$  (amplitude of the arrival function) will be varied as a source of external dynamics (e.g., stronger seasonal effects by varying order volumes of customers). Higher values of  $\mu^k$  lead to stronger variations and a more dynamic situation. In this experiment  $\mu^k$  is the same for every category  $k$  in one simulation run.

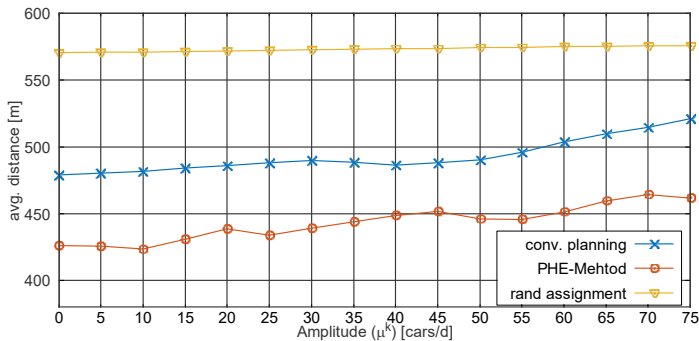


Figure 7: Simulation results for varying amplitudes

Figure 7 shows the average driving distance of all cars in a simulation run for the conventional planning, the pheromone based autonomous control method and the random assignment. The values of  $\gamma_{1-4}$  have been set to ( $\gamma_{1-3} = 0.1$  and  $\gamma_4 = 0.4$ ). The role of this parameters will be discussed later in section 5.2. As expected, the random assignment performs worst. Due to the random assignment possible short routes between source, storage area and sink are neglected. This leads to long driving distances. Figure 7 shows that this method is not affected by an increasing amplitude. By contrast, Figure 7 depicts a strong dependency between the conventional planning and the amplitude of the arrival function. A higher amplitude causes stronger peak periods with higher amount of arriving cars. In this situation cars are assigned to the pattern shown in Figure 6. The higher the incoming volume in a peak period, the more often secondary assignments (peak reserve) are used and occupy parking areas of other models (primary assignment) with potentially shorter routes. This leads to longer routes un-

der dynamic arrival conditions. Compared to the conventional planned situation the autonomous control method behaves different. Although, the average driving distance increases with higher values of  $\mu^k$ , this effect is slightly lower compared to the conventional planning. The autonomous control method is able to cope with the external dynamics more robustly. Regarding the absolute values, the autonomous control method outperforms the conventional planning for every  $\mu^k$ . This effect is stronger for higher values of  $\mu^k$ . Despite higher external dynamics the autonomous control method is able to find suitable row assignments with shorter routes. As described in section 3, the implementation of bulked departures can be seen as a source of additional dynamics. Figure 8 depicts simulation results for the scenario with bulked departures. For Figure 8, the mean vessels' capacity has been increased in steps of 100 cars per vessel (starting from 500 car up to 2000 cars per vessel). Every simulation run had a fixed mean arrival  $\lambda^k$  (see Table 1) and an amplitude of  $\mu^k = 50$  cars per day in order to provide comparability with Figure 7. As already discussed, bigger ship capacities lead to longer inventory times. These longer inventory times affect the overall performance negatively. This can be confirmed by Figure 8. It shows that bigger vessels' capacity increase difference between conventional planning and the new autonomous control method. Like in the first scenario, the autonomous control method outperforms the conventional assignment. For vessels' capacity of 500 vehicles, the average driving distance is about 3.8% higher for the conventional planning. By contrast, this gap is for vessels' capacity of 2000 cars 11.35% higher compared to the autonomously controlled situation. In total, Figure 7 and Figure 8 confirm the hypothesis that autonomous control improve the terminals' performance under increasing external dynamics conditions induced by volatile demand

fluctuations (Figure 7) and varying bulked departures (Figure 8). Comparing both types of dynamics, the impact of varying amplitudes seems to be stronger than the vessels' capacity. Both sources of dynamics lead to differences in the internal systems' behavior for the autonomous control method and the conventional planning.

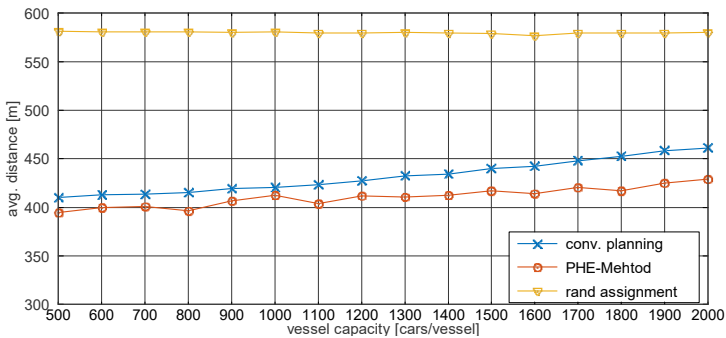


Figure 8: Simulation results for vessel capacities

Figure 9 confirms the impact of increasing dynamics on the conventional yard assignment and on the autonomous control method.

It presents scatter plots for the pheromone based method and for the conventional planning. Each plot depicts the driving distance against the terminals inventory for different points in time in a simulation run. The terminals inventory is an indicator for the externally induced dynamics. In both cases (autonomous control and conventional planning) the systems inventory level is defined by the arrival and the departure function (see also Figure 4 and Figure 5). There is no influence of the control methods on the inventory over time. Thus, this measure can be seen as an indicator of external dynamics. In addition, Figure 9 presents the average driving distance related to the terminals inventory at the same time. The driving distance

depends directly on the control methods behavior. It can be seen as an indicator of the response of the control method to the corresponding external dynamics. Both upper graphs of Figure 9 show the scatter plots for the pheromone based method and the conventional planning in the scenario with a constant departure rate. Both graphs have been recorded for simulation runs with an arrival amplitude of  $\mu^k = 50$ . Figure 9 shows that the conventional planning leads to lower and smaller range of average driving distances. By contrast the driving distance recorded with the pheromone based method seems to follow the inventory level. It is able to realize smaller average driving distances for situations with a low and a high inventory level and forms a nearly circular pattern. This pattern can be explained by the predefined departure delay in the scenario with constant departures. Cars arriving in situations with lower inventory levels have a better chance to be assigned to a parking row with a shorter overall driving distance. Due to the departure delay these cars leave the system later in time. At this time the inventory level may be higher as it was at the time of the assignment to a row.

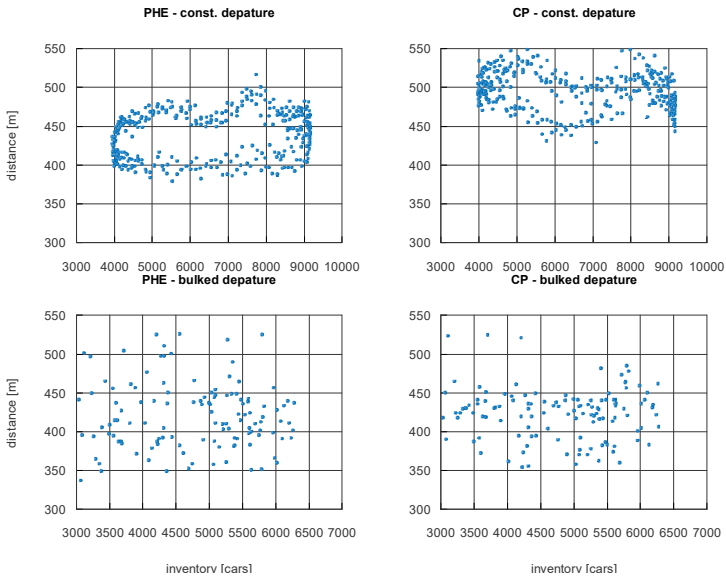


Figure 9: Scatter plots - driving distance against terminal inventory levels

Thus, Figure 9 shows a shorter driving distance of higher inventory levels and vice versa. A similar effect can be recognized for the conventionally planned situation. The graphs at the bottom of Figure 9 show the results for the scenario with bulked vessel departures (with vessel capacity of 1000 cars per vessel). Both scatter plots show a different systems behavior compared to the situation with the constant departure rate. Again the conventional planning leads to a smaller range of distances for all recorded inventory levels. However, no periodic effects can be recognized. Due to the bulked departure of cars the average inventory level is lower compared to the situation with constant departures.

Arriving ships reduce the inventory level in an abrupt manner. Cars arriving after the departure of a ship can directly be assigned to parking rows with shorter overall driving distances. Thus, the dependency of the driving distance is lower in the scenario with bulked departures. The same effect can be recognized for the pheromone based method. Driving distances and inventory levels are dispersed in the corresponding plot in Figure 9. However, the mean driving distance is still lower compared to the conventional planned situation (see also Figure 8).

## 5.2 Variations of Pheromone Weighting Factors

For the simulation runs presented in section 5.1. all weighting factors ( $\gamma_{1-4}$ ) of equation (2) have been set to values, which performed well in some pretest simulation runs. In this section the impact of these weighting factors will be addressed.

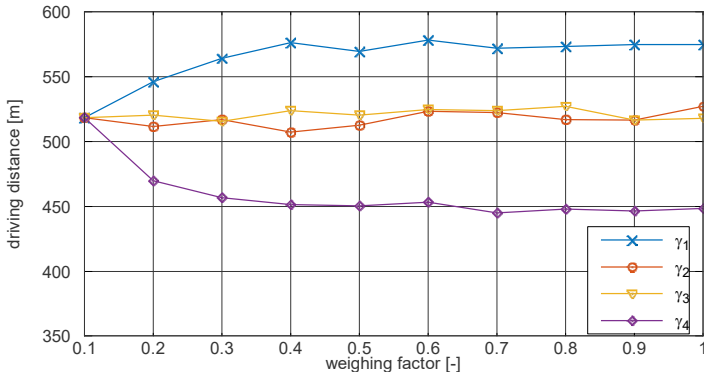


Figure 10: impact of weighting factors  $\gamma_{1-4}$

Therefore, Figure 10 presents results for variations of these weighting factors regarding its impact on the average driving distance. All other values of the weighting factor have been set to 0.1 while increasing a particular weighting factor.

The first weighing factor addresses the balancing between estimated inventory times and estimated driving distances of vehicles categories. An increase of this factor leads to potentially longer driving distances. In this case equation (2) prefers a stronger balancing. It does not emphasize a greedy generation of short routes. This effect can be observed in Figure 10. As expected, the factors  $\gamma_{2-3}$  have a low impact on the average driving distance. Both factors aim at reducing the dispersion of vehicles of the same category on a terminal.

The fourth factor  $\gamma_4$  aims at reducing the driving distance for every category of cars. Accordingly, Figure 10 shows clearly the impact of this factor on the average driving distance. In total Figure 10 shows that each term of equation (2) has its desired impact on the total driving distance.

## 6 Summary and Outlook

This paper presented shortcomings of conventional yard planning approaches and assumed that autonomously controlled processes could improve the performance of automobile terminals. It presented a combined bounded rational autonomous control approach with a pheromone based strategy. Furthermore, it introduces a generic modeling approach for automobile terminals for analysis of different scenarios. In the case at hand, a sinusoidal arrival function has been used to model a volatile arrival rates of

vehicles. In this scenario the new autonomous control method outperformed a simple conventional yard assignment. The analysis showed that the new autonomous control method performs best in highly dynamic situations. Moreover, this paper showed that the underlying parameters of the autonomous control method can be used to adjust the methods performance according to logistics targets of the terminal.

These results motivate for further and deeper research. First of all, a systematic investigation of structural parameters like, terminals size, distances, location of sources and sinks seems to be promising for getting a comprehensive understanding of the performance of autonomously controlled terminal processes. Although this paper showed that autonomous control is able to outperform a simple rule based yard assignment, further research will focus on more sophisticated planning methods (i.e. algorithmic approaches) and on more realistic parameters like complex OEM's model destinations mixtures and the diversified ship schedules with multiple destinations. A third research direction will be the implementation of autonomous decisions of other logistics objects like ships or trucks as well as the implementation of further autonomous control strategies.

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