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Dynamic Control of Multiple Vehicles Moving Along the Same Rail in Automated Vehicle Storage and Retrieval Systems

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Abstract

The emerging trend towards increased flexibility and throughput capacity of automated warehouses is pushing the implementation of rail-guided automated vehicle storage and retrieval systems (AVSRSs). Especially in tier-captive AVSRSs, where horizontal and vertical transport is largely separated, high throughput capacities can be achieved. However, by deploying more than one vehicle on each tier, the performance of those systems can be further increased and thus transformed into high-powered AVSRSs. In this work, we present an algorithm which provides for the efficient and yet robust dynamic control of multiple vehicles moving along a common rail on a tier. By conducting a simulation study, we show the performance improvement of horizontal transportation in high-powered AVSRSs by analyzing different allocation strategies.

Keywords: automated vehicle storage and retrieval systems; shuttle systems; dynamic control; allocation strategies; discrete-event simulation

1. Introduction

Due to rapidly changing environments, today's automated warehouses are faced with a growing demand for flexibility as well as throughput capacity. One way to address this rising trend is the application of automated vehicle storage and retrieval systems (AVSRSs), also known as shuttle systems. This upcoming technology is used for storing transportation units to supply picking or manufacturing areas by applying the goods-to-person principle (FEM, 2017).

In AVSRSs with tier-captive vehicles, horizontal and vertical transport tasks are executed by shuttle and lift vehicles. Since the transports are largely decoupled from each other, this type of AVSRS is able to achieve the highest throughput. Shuttle vehicles hand over the transportation units to transfer buffers and do not have to wait for lift vehicles and vice versa. In order to further increase throughput capacity as well as to provide enhanced scalability at the individual tiers of new or even already existing AVSRSs, more than one shuttle vehicle on each tier can be deployed (see Figure 1).

However, such high-powered AVSRSs with multiple vehicles on a single tier require a more complex control algorithm to run the system in a robust and efficient manner. As a consequence, the applied control algorithm has to address the following main challenges:

- Which transport task should be executed by which shuttle vehicle?
- How can safe execution without any block

events or collisions with other shuttle vehicles be ensured?

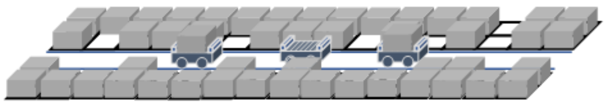

Figure 1. Multiple shuttle vehicles moving along a common rail on a tier of a high-powered AVSRS

The paper is structured as follows. In the second section, a literature review in the respective areas is presented. In section 3, the applied control algorithm is described and in section 4, the developed allocation strategies are presented. In section 5, the performed simulation study is presented. In section 6, a conclusion and an outlook are provided.

2. Literature Review

Since in high-powered AVSRSs, several vehicles move along the same rail on each tier, vehicles may block or even collide with each other during operation. In order to prevent this, a control algorithm needs to be applied that coordinates the vehicles in a robust and efficient way.

By introducing the shuttle vehicle scheduling problem, Habl, Lienert, Pradines, and Fottner (2019) present different approaches for coordinating multiple vehicles with non-crossing constraints, i.e. vehicles that cannot pass each other. In the field of high-powered AVSRSs, several scheduling algorithms based on block sequencing have been applied to lift vehicles by Habl, Balducci, and Fottner (2019) and to shuttle vehicles, as introduced in Habl, Plapp, and Fottner (2019).

As an alternative to those rigid and computation-intensive scheduling algorithms, a dynamic control could be applied to those systems. However, control strategies to efficiently allocate transport jobs to vehicles and to ensure safe job execution by the vehicles, need to be applied when using a dynamic approach. In literature, allocation strategies in AVSRS are widely discussed and, in this respect, priority rules are applied. Marchet, Melacini, Perotti, and Tappia (2012) address AVSRS with unit lifts and Malmborg (2002) studies AVSRS with vehicle lifts which are both controlled based on the *first come first served* principle.

When it comes to execution of the transport job, different approaches from other areas can be considered. In the field of multi-car elevators, Ishihara and Kato (2013) apply a dynamic zoning approach which dynamically assigns a zone to each lift vehicle to prevent collisions, and Takahashi, Kita, Suzuki, Sudo, and Markon (2003) use a genetic algorithm to define optimal zone partitioning. In rail services, fixed track sections which can only be used by one train at a time are applied to ensure that transport on the tracks is safe (Maschek, 2018). In AVSRSs, a time window routing method has been applied to shuttle systems in order to ensure an efficient and robust operation of those systems in Lienert and Fottner (2017). Roy, Krishnamurthy, Heragu, and Malmborg (2016) study blocking effects on autonomous vehicles and develop protocols to address block events that occur.

When studying complex configurations of AVSRSs, throughput analysis is usually carried out by simulation. Lerher, Ekren, and Sari (2015) perform a simulation study to analyze the impact of different parameters on the throughput capacity of an AVSRS. In order to identify the ideal layout, Zhao, Luo, Zhang, Lodewijks (2016) present a simulation model of an AVSRS to analyze rack configurations with multiple lifting systems.

3. Dynamic Control Approach

In order to prevent block events and collisions between shuttle vehicles $\{v_1,v_2,\ldots,v_m\}$, the rail is divided into sections $\{s_1,s_2,\ldots,s_n\}$ and their occupancy is tracked by sensors at the section boundaries. One section may be used by only one vehicle v_i at a time. It is only possible to enter a section after reserving this section in advance (see Figure 2).

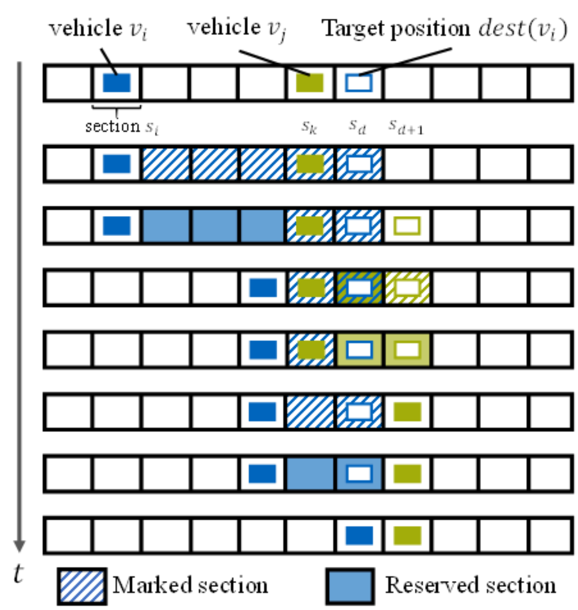

Figure 2. Schematic representation of the marking and reservation process

As soon as a vehicle v_i receives a transport job with the target position dest(v_i), it starts the marking process. It begins from the currently occupied section s_i and iterates over all sections to the target position. Thus, the sections s_{i+1} (first section not occupied by the vehicle in the direction of the target) up to and including dest(v_i) = s_d are marked. The marking can be conducted at any time and it is performed by using the start time of the job, i.e. the time at which the job is activated for the vehicle. After that, it is iterated again over all marked sections, and a reservation attempt is started for each section. The reservation of a section s_j by a vehicle v_i is only possible if:

- The section s_j under consideration is not occupied.
- The section s_j under consideration is not reserved.
- Order journey: Vehicle v_i has marked section s_j in the first place (earliest marking).
- Evasion journey: The earliest marking of section s_j is from the vehicle, which is the initiator of the evasion of vehicle v_i.
- Special case: All sections to the destination are available (neither reserved nor occupied). In this instance, all sections are reserved immediately.

If a section s_k cannot be reserved, the reserving iteration is stopped and sections are reserved only up to section s_{k-1}. If section s_k is occupied and the following conditions apply, an evasion task can be initiated:

- The vehicle v_j on section s_k does not move and it is currently not busy handing over a unit.
- The destination of the blocking vehicle dest(v_j) is not in the direction of the target of the vehicle v_i.
- Order journey: Vehicle v_i has marked in the first place (earliest marking).
- Evasion journey: The earliest marking is from the vehicle, which is the initiator of the evasion of vehicle v_i.

If the conditions for an evasion task from vehicle v_i to vehicle v_j are met, vehicle v_j receives a task with the following target position: dest(v_j)=dest(v_i)+1=s_{d+1}. Vehicle v_j is therefore asked to go to the first position behind the destination position of vehicle v_i.

After the reservation attempt, the vehicle departs along the route as far as it has been reserved and starts a new reservation attempt from there.

If a vehicle with an active order is on an evasion journey and the actual order destination is on its way to the evasion position, a stopover is made at the order destination, and the order is handled by receiving or dispensing the unit. After that, a further journey to the evasion position takes place.

The vehicle speed depends on the distance that could be reserved. It is checked whether a trapezoidal journey is already possible on the reserved and drivable distance d_{res}=[s_{i+1},s_k] by applying vehicle acceleration (a_{acc}) and deceleration (a_{dec}), i.e. whether the following equations (1)-(2) are satisfied:

$$d_{res} \geq d_{acc} + d_{dec} \tag{1}$$

$$d_{acc/dec} = \frac{1}{2} * \frac{{v_{max}}^2}{a_{acc/dec}} \tag{2}$$

If this condition is met, the vehicle is able to accelerate to the maximum speed v_{max}. Otherwise, the speed is set for a triangular journey as in equation (3):

$$v = \sqrt{2 * d_{res} * \frac{a_{acc} * a_{dec}}{a_{acc} + a_{dec}}} \tag{3}$$

If the section length is smaller than the vehicle length, it must be verified that all sections occupied at any time are marked and reserved. The vehicles are then located at the start and target positions on more than one section. The iteration is carried out accordingly from the first section that is no longer occupied in the start position to the front section occupied in the target position. When determining the evasion position, the assignment of more than one section at the target position must be observed.

As illustrated in Figure 3 by means of an exemplary setup for the marking and reservation process, the vehicle v_1 iterates over the sections s_{i+1} to dest(v_1) = s_{i+5} in order to mark them. After that, the iteration is restarted in order to reserve them. This two-step process is necessary, because only connected sections with the earliest marking can be reserved. In this sense, the sections s_{i+1} up to s_{i+3} are reserved. Section s_{i+4} is already occupied by vehicle v_2. However, since conditions are met, vehicle v_1 can issue an evasion task to vehicle v_2. The target position of that task is the section behind the destination of vehicle v_1, i.e. dest(v_2)=dest(v_1)+1=s_{i+6}.

While vehicle v_2 now starts the marking and reservation process to section s_{i+6}, vehicle v_1 travels the previously reserved distance, i.e. up to section s_{i+3}. Once there, a reservation attempt is started again. Assuming that vehicle v_2 has now reached its target position dest(v_2)=s_{i+6}, vehicle v_1 can now reserve sections s_{i+4} and s_{i+5}, and starts the journey to its target position.

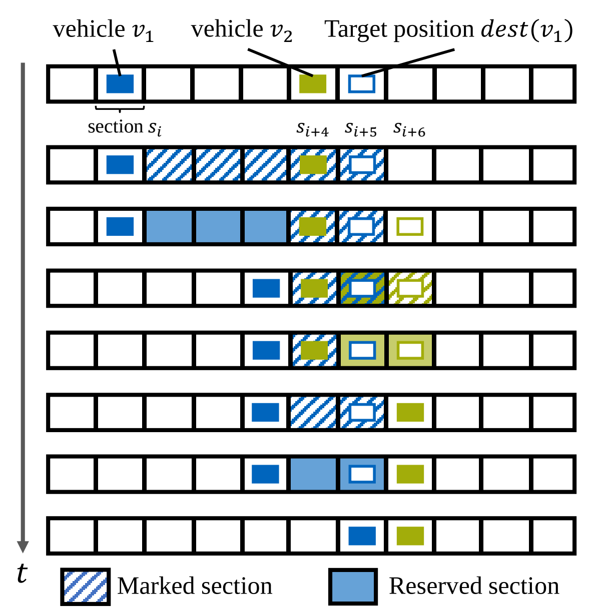

Figure 3. Exemplary setup for the marking and reservation process

4. Allocation Strategies

All developed allocation strategies are induced by a job. This means that a new activated storage or retrieval job searches for a vehicle according to certain priority rules and is assigned to it. The number of vehicles from which a choice is made includes all vehicles, and not just those currently free. Hence, there are job queues for each vehicle.

4.1. Random Vehicle (RANDOM)

The job is randomly assigned to a vehicle.

4.2. Nearest Vehicle First (NVF)

The distance of each vehicle position to the position where the vehicle would need to start the job is crucial. Since in the model there are all vehicles in the selection set, the considered vehicle position differs depending on their status of themselves:

- busy: the position where the vehicle finishes its last currently assigned job is relevant
- idle: the current position of the vehicle is relevant
- idle and in evasion: the final evasion position is relevant

The vehicle v_j whose relevant position has the smallest distance d_j to the job start position is selected from all vehicles i (see equation 4).

$$d_j = \min_{\forall i}\{d_i\} \tag{4}$$

4.3. Least Utilized Vehicle (LUV)

That vehicle is selected which has the lowest utilization at the current time. The utilization is measured by the entire idle time of the vehicles. The vehicle with the longest total idle time or lowest utilization U_j is selected among all vehicles i (see equation 5).

$$U_j = \min_{\forall i}\{U_i\} \tag{5}$$

4.4. Longest Idle Vehicle (LIV)

This strategy primarily selects vehicles i that are currently available. If one or more vehicles are idle, the one that has the longest current idle time t_j is selected from this set. If there is no vehicle in an idle state, the decision is made according to LUV.

Out of all free vehicles i, the vehicle is chosen as in equation (6):

$$t_j = \max_{\forall i}\{t_i\} \tag{6}$$

With $t_i = T_{current} - T_{idle}$, where $T_{current}$ is the current time and T_{idle} is the time at which the vehicle has been set to idle.

4.5. NVF with Idle Priority (NVF-IdlePrio)

This modification of the NVF strategy aims to achieve a more uniform utilization of the vehicles. At the beginning, only those vehicles which are currently available (idle) are considered, and from this set, the one with the smallest distance to the job start position is selected. If no vehicle is idle, all vehicles will be considered.

4.6. NVF with Task Maximum (NVF-TaskMax)

This modification of the NVF strategy also aims to balance the utilization of the vehicles. In this strategy, this balance is ensured by a predetermined task maximum per vehicle at a time, which is defined by equation (7):

$$TaskMax = \left\lceil \frac{\max(n_{activated\ jobs})}{n_{vehicles}} \right\rceil \tag{7}$$

5. Simulation Study

In this section, we analyze the efficiency of the described control approach combined with the allocation strategies, by performing a simulation study. By considering an AVSRS, each of the developed allocation strategies is applied and the number of shuttle vehicles varied.

5.1. Model

The simulation model was created by using the discrete-event simulation software Tecnomatix Plant Simulation. In essence, the modeled AVSRS consists of one aisle that has lifting systems and tiers which are connected to each other by transfer buffers. Each buffer is dedicated to storage or retrieval. In lifting systems, lift vehicles accomplish the vertical transportation of units by transporting units from the input/output (I/O) point to the transfer buffer of the respective tier (storage) and vice versa (retrieval). Whereas in tiers, shuttle vehicles carry out the horizontal transportation of the units by transporting units from the transfer buffer to the respective bay (storage) and vice versa (retrieval).

In our study, we focus on the performance improvement of horizontal transportation in an aisle of an AVSRS. In order to prevent throughput limitation by vertical transportation, we configure the warehouse by only one tier and several lifting systems. In order to compare the developed allocation strategies, a simulation experiment for every strategy is performed. In each experiment, the number of vehicles is varied from 1 to 5 and 400 storage and retrieval jobs are created randomly. As derived in a preliminary study, with a 95% confidence interval for throughput, the number of generated jobs is considered as sufficient. For each experiment, three replications are conducted. In each simulation experiment and replication, respectively, the system is initialized and the defined number of transport jobs (storage and retrieval jobs) for the warehouse are created and assigned to the vehicles according to the developed allocation strategies. Finally, the throughput capacity of the warehouse is calculated by measuring the time needed for completion.

5.2. Parameters

For the simulation, we study an exemplary AVSRS, created by parameterizing the model. The applied parameter specifications of the considered AVSRS are shown in Table 1.

Table 1. Simulation parameters

Rack	
Number of aisles	1
Number of tiers	1
Storage depth	1
Number of bays per tier	200
Distance between bays	0.5 m
Tier	
Length	50 m
Number of shuttle vehicles	1-5
Shuttle vehicle	
Velocity	2 m/s
Acceleration	2 m/s²
Deceleration	2 m/s²
Pick-up time	3 s
Safety distance	0.1 m
Length	1 m
Lifting system	
Number per aisle	2
Position in aisle	Front
Number of I/O points	1
Number of lift vehicles	1
Lift vehicle	
Velocity	2 m/s
Acceleration	2.5 m/s²
Deceleration	2.5 m/s²
Pick-up time	2.5 s

5.3. Results

In the following simulation results, we analyze throughput capacity and mean utilization depending on applied allocation strategy and the number of shuttle vehicles deployed.

Figure 4 shows the obtained throughput by applying the different allocation strategies described in section 4. It transpires that the throughput capacity of the considered AVSRS can be significantly increased by deploying more than one vehicle on the tier. The highest throughput of 176 jobs per hour can be achieved by applying NVF-TaskMax and deploying four vehicles. This results in a total surge of 49% compared to the throughput capacity of a single vehicle (118 jobs per hour). As can be seen, besides NVF-TaskMax, the strategy NVF-IdlePrio constantly achieves the highest throughput capacities. However, the throughput of the NVF strategy stagnates when deploying more than two vehicles. By applying the strategy LIV, the throughput capacity increases in particular when deploying a high number of vehicles. On the other hand, when applying the strategy LUV, the throughput is even lower than the reference strategy RANDOM. Overall, it can be observed that due to route optimization, the allocation strategies based on modified NVF achieve the highest throughput. However, with an increasing number of vehicles, a uniform utilization of the vehicles in the LIV strategy is gaining in importance.

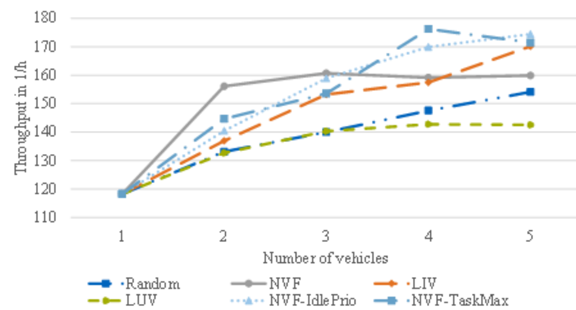

Figure 4. Throughput depending on applied allocation strategy and deployed number of vehicles

To this effect, Figure 5 shows the mean utilization of the vehicles by applying the different allocation strategies. When applying the strategies NVF-IdlePrio or NVF-TaskMax, vehicle utilization only slightly decreases as the number of vehicles increases. In NVF-TaskMax, the noticeable increase in utilization when the number of vehicles is increased from three to four vehicles is considered as an outlier which is based on inefficient roundings of equation (7) when deploying three vehicles. On the other hand, utilization reduces sharply when applying NVF strategy, which complies with the observed throughput capacities. This can be explained by inactive vehicles, which are waiting at the evasion area for extended periods. Especially when deploying a higher number of vehicles, vehicle utilization of the strategy LIV is among the highest.

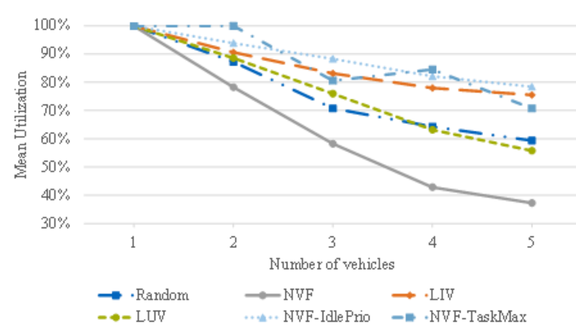

Figure 5. Mean utilization of the vehicles depending on applied allocation strategy and deployed number of vehicles

In a general sense, Figure 6 shows the mean throughput achieved by the different allocation strategies and the mean distance traveled by deploying 1 to 5 vehicles. When applying the strategies NVF-IdlePrio or NVF-TaskMax, the highest average throughput can be obtained. However, by analyzing

NVF strategy, it turns out that a short mean traveled distance does not imply a high throughput capacity, especially if vehicle utilization is not optimized by the strategy.

In this respect, the allocation strategies with the highest achieved throughput capacity (NVF-IdlePrio, NVF-TaskMax) utilize vehicles to a greater extent, i.e. above 85%, compared to the other strategies (Figure 7). As a result, an allocation strategy that simultaneously optimizes traveled distance as well as utilization turns out to be the most promising approach when optimizing throughput capacity.

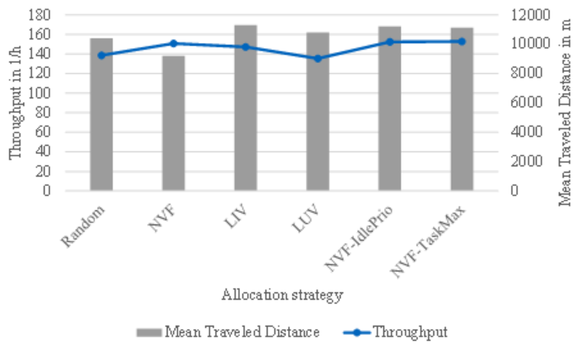

Figure 6. Mean throughput and mean distance traveled by deploying 1 to 5 vehicles and applying different allocation strategies

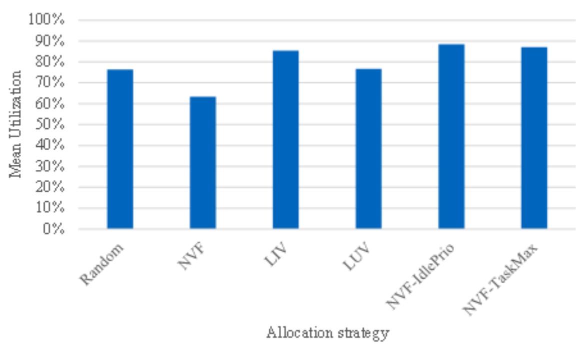

Figure 7. Mean vehicle utilization by deploying 1 to 5 vehicles and applying different allocation strategies

6. Conclusion and Outlook

In this paper, a dynamic control approach for the robust and efficient coordination of shuttle vehicles in a tier of a high-powered AVSRS is presented. By using an algorithm based on section reservation, block events and collisions can be completely avoided. In order to increase the efficiency of job execution, different allocation strategies were developed and evaluated in a simulation study.

For this purpose, a simulation model of an AVSRS was created. By conducting a series of simulation experiments, the following main results were identified:

- The throughput capacity of an AVSRS can be significantly increased by deploying more than one shuttle vehicle on each tier. This could improve the efficiency of AVSRS in industrial practice, where usually only one shuttle vehicle on each tier is deployed until now.
- The allocation strategies NVF-IdlePrio and NVF-TaskMax achieve the highest throughput by optimizing traveled distance as well as vehicle utilization.

In future work, the developed algorithm will be also applied in lifting systems of AVSRSs. This allows more than one lift vehicle to be deployed in a lifting system, and thus increases the throughput capacity of lifting systems, too. Since lifting systems mostly limit the throughput capacity of AVSRSs in common configurations of industrial practice, the overall throughput capacity of these warehouse systems can be further increased.

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