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A Multi-objective Optimization Approach

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Platooning of Automated Ground Vehicles to Connect Port and Hinterland: A Multi-objective Optimization Approach

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Abstract. Automated ground vehicles (AGVs) are essential parts of container operations at many ports. Forming platoons—as conceptually established in trucking—may allow these vehicles to directly cater demand points such as dry ports in the hinterland. In this work, we aim to assess such AGV platoons in terms of operational efficiency and costs, considering the case of the Port of Rotterdam. We propose a multi-objective mixed-integer programming model that minimizes dwell and idle times, on the one hand, and the total cost of the system involving transportation, labor, and platoon formation costs, on the other hand. To achieve Pareto optimal solutions that capture the trade-offs between minimizing cost and time, we apply an augmented epsilon constraint method. The results indicate that all the containers are delivered by AGVs. This not only shortens the dwell time of the containers by decreasing loading/unloading processes and eliminating stacking but also leads to considerable cost savings.

Keywords: Platooning · Automated ground vehicles · Container terminals · Loading/unloading operations · Emission analysis

1 Introduction

Platooning of trucks has received significant attention in recent years because of its potential to reduce costs and emissions while preparing the ground for fully automated road transport. Automated Ground Vehicles (AGVs) have been used at many ports for several decades. While early generations were exclusively guided vehicles, newer generations of AGVs have been gradually adopting autonomous technologies. This growing trend has led researchers and practitioners to rethink the application of AGVs, especially considering their use in

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an extended area of the port hinterland, possibly avoiding time-consuming and cost-intensive loading processes at container terminals. Smaller terminals and ports with adjacent dry ports, or generally, smaller subsets of containers handled at larger terminals could benefit from such ideas. Nonetheless, most roads are not yet ready and are not expected to be ready in the short or mid-term to safely be used by AGVs. In this expected transition period, vehicle platoons are considered a viable option for early adoption autonomous vehicle technology.

The concept platooning has been investigated by researchers as a way to benefit from automation in this transition phase [1]. For instance, Larrson et al. [12] have developed an approach to assess fuel savings achieved by truck platoons and more recently, Scherr et al. [17] have demonstrated how platoons can be used to bring AGVs from one autonomous zone to another. However, AGVs delivering containers from a ship to the hinterland directly, and thereby avoiding the traditional storage option (as illustrated in Fig. 1), still needs to be particularly investigated.

With the present work, we aim to make a first step towards evaluating the actual potential of applying AGV platoons in such settings. For this purpose, we develop a multi-objective mixed-integer programming model where AGV platoons are considered as transfer modes between ports and autonomous hinterland areas. We obtain Pareto optimal solutions using an augmented epsilon constraint method and obtain significant gains in terms of total costs, dwell times, and emissions, when AGV platoons are employed.

2 Related Work

Being integral parts of contemporary logistics systems, Automated Ground Vehicles (AGVs) are used to transport and handle various goods in diverse industrial environments over five decades. Especially in port terminals, AGVs are established transport modes typically transferring containers between ships and storage areas on land. The majority of research focuses on operation-level planning problems such as AGV scheduling [3,4,10], as well as routing [5]. For their solution, there exist a plethora of diverse studies that propose mathematical models, exact and heuristic approaches with the aim of minimizing mainly the container dwell times. Table 1 provides a comparison among relevant articles considering various aspects. For a comprehensive review on AGV scheduling and routing the reader is referred to Qiu et al. [15].

New technological advances have motivated recent research efforts to incorporate traffic control (e.g. collision avoidance mechanisms) into the planning process of AGVs in container terminals. Zhong et al. [21] study the integrated scheduling and path planning problem, while preventing potential conflicts among AGVs. To solve the problem, a mixed integer programming model along with two heuristic methods are introduced. Experiments with different numbers of containers and AGVs verify the potential of the proposed approach to minimize the delay of AVGs in large-scale problem settings.

Xin et al. [19] investigate the collision-free trajectory planning of free-ranging AGVs combined with the scheduling of different types of equipment for container

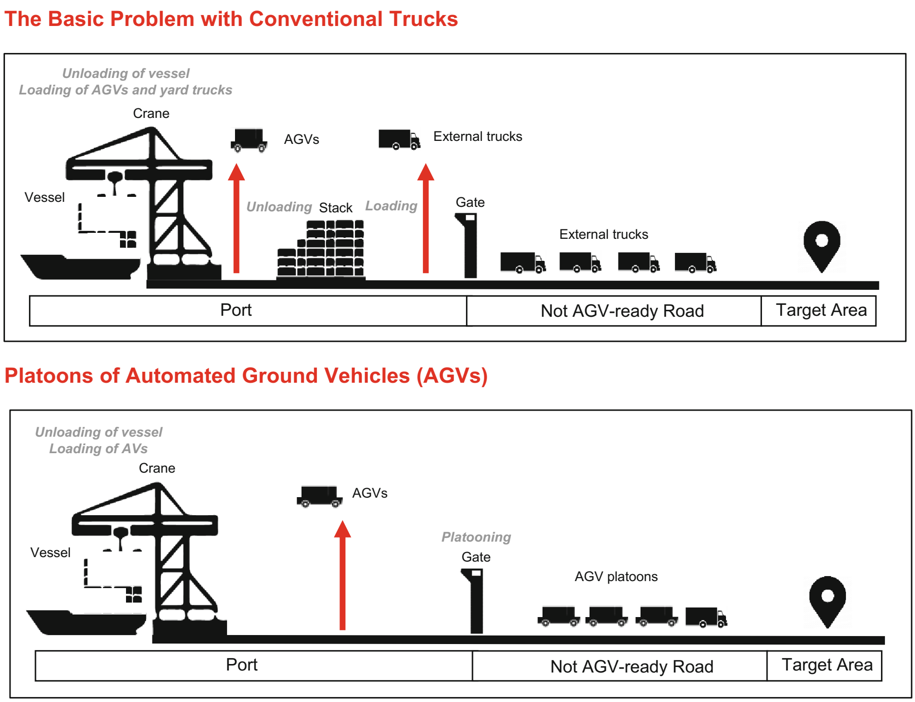


Fig. 1. The container drayage process with conventional trucks or AGV platoons

Table 1. Articles on automated ground vehicles and platooning

Reference	Objective		Problem		Method		Feature		Vehicle type	
	Time	Fuel	R	SC	EX	H	PL	TC	AGV	TR
Boysen et al. [2]		√		√	√		√			√
Briskorn et al. [3]	√			√	√	√			√	
Cheng et al. [4]	√			√	√			√	√	
Corréa et al. [5]	√		√	√		√		√	√	
Kim et al. [10]	√			√		√			√	
Larson et al. [11]		√	√		√		√		√	
Larsson et al. [12]		√	√		√	√	√			√
Scherr et al. [17]	√		√			√	√		√	
Xin et al. [19]	√			√		√		√	√	
Zhang et al. [20]	√	√		√	√		√		√	
Zhong et al. [21]	√			√		√		√	√	
This paper	√	√		√	√		√		√	

Problems: R (Routing), SC (Scheduling)
Methods: EX (Exact), H (Heuristic)
Features: PL (Platooning), TC (Traffic control)
Vehicle types: AGV (Automated Ground Vehicle), TR (Truck)

transport. The proposed approach determines the sequence of jobs per piece of equipment by solving a hybrid flow shop scheduling problem. Based on the resulting sequences, conflict-free trajectories are identified by solving a series of mixed integer linear programming problems sequentially. The performance of the developed algorithm is evaluated by a simulation study, which shows that no collisions occur while the distance covered by the AGVs is significantly reduced.

Up-to-now, theoretical and practical studies have embraced AGVs for container transport only between ships and terminal storage areas. Hence, to the best of our knowledge, there is no approach that considers AGVs delivering containers from a ship to the hinterland directly, thereby avoiding the traditional storage option. Moreover, in these studies, AGVs are assumed to function in the restrained environment of a container terminal. Therefore, forming platoons of AGVs to render their operation feasible in non-controlled environments (e.g. public roads) is a new concept that has not been so far taken into consideration.

Platooning has emerged as a promising technology that not only offers significant fuel savings, but also prepares the ground of increased autonomy in freight transportation (Janssen et al. [9]). Research developments in the area, especially platooning problem classifications, operations research models and solution methods, are reviewed in Bhoopalam et al. [1]. A large part of the relevant literature has been devoted to technical and technological aspects of platooning including string sequence and stability, signal timing, longitudinal trajectory control, speed profile, connectivity issues, obstacle avoidance, vehicle-to-vehicle communications. However, none of these aspects is investigated in the current research. More information on these topics can be found in the works of Delimpaltadakis et al. [6], Liang et al. [13], and Zhong et al. [22].

Studies on the operational side of platooning, such as planning, routing, and scheduling, are still scarce in the logistics literature [7]. A first attempt to explore the benefits of platooning is presented in Larsson et al. [12]. The main objective is to maximize the fuel savings while considering the formation and routing of the platoon. In this study, several linear programming formulations for different problem variants are proposed with the aim of solving small instances. Experimental results show the gains of optimal platoon routing in fuel efficiency. For the same platooning problem, an improved model is developed in Larson et al. [11]. This approach results in a significant reduction of the problem size, thereby enabling to tackle realistic instances more efficiently.

Different aspects of the platoon formation problem are analyzed in Boysen et al. [2]. To this end, the authors formulate a basic platooning problem that addresses the truck-to-platoon assignment under the assumption that each truck considers an individual delivery window and the resulting platoons share the same path. Their computational analysis shows that the benefits of platooning on fuel consumption depend significantly on the number of platoon partners, restrictions on the platoon length as well as the size of the delivery windows. In the study of Zhang et al. [20], a platoon coordination and scheduling problem in the presence of travel time uncertainty is investigated. The problem is solved to optimality via an analytical model that considers different converging and diverging route networks. The authors conclude that differences in the scheduled arrival times of vehicles renders platooning an inefficient option.

A parcel delivery problem tackled via the use of heterogeneous autonomous fleets is introduced in Scherr et al. [17]. Autonomous vehicles travel only in specific zones while they are guided by manually operated vehicles forming platoons elsewhere. To the best of our knowledge, this is the only study in the literature where platooning plays a transfer mode role by connecting autonomous and ordinary driving zones. To model the problem, a linear programming formulation is proposed. Additionally, the problem complexity is reduced by utilizing a time-expanded model that discretizes the considered planning horizon.

In overall, despite the increasing interest on platooning, there is a limited number of research works in the freight transportation sector. This provides ample opportunities, especially for new decision making approaches that investigate its role in a wide spectrum of logistics applications. So far, platoon formation, scheduling and routing problems have claimed most of the research attention, while the role of platooning as a transfer mode still remains heavily unexplored. Moreover, up-to-now, fuel costs have been the main focus of platooning problems. Considering other types of cost will reveal the impact of platooning on additional aspects, thereby unlocking its full potential.

3 A Model for AGV Platooning

The proposed framework deals with container delivery from a port to its hinterland depot or adjacent dry port, henceforth referred as target zone. In the classic container terminal process, after unloading a vessel, its containers are moved to stack to wait for the rest of their delivery journey. Assume that a subset of these containers can be directly delivered to their target zone, without entering the stack, by application of external AGVs which belong to the carriers. For this subset of the containers, denoted as I in our model, we will investigate if direct delivery can bring savings in dwell time and costs. The transportation network is considered to be heterogeneous where the port and the target zone are appropriate for automated driving and the linking road segment which connects these two areas together is not suitable for AGVs. Therefore, the AGVs have to join a platoon with a human-driven leader to move in this linking road segment. Dwell time for either of the two delivery modes ($n = 1, 2$, 1 representing the classic delivery by trucks in presence of stacking and 2 by AGVs) is the accumulation

Table 2. Dwell time in two delivery modes

Dwell time	
Delivery by truck ($n = 1$)	Delivery by AGV ($n = 2$)
Loading containers on AGVs (t_1) Traveling to stack (t_2)	Loading containers on AGVs (t'_1)
Unloading containers off AGVs (t_3) Stacking (t_4)	Traveling to gate (t'_2)
Loading containers on trucks (t_5) Traveling to gate (t_6)	Joining platoons (t'_3)

of the time components shown in Table 2. t_1, t_2, t_3, t_5, t_6, t'_1, t'_2, and t'_3 are fixed known parameters, whereas t_4 is a variable determined in the model.

The idea is to specify optimal transportation modes and schedules that minimize delivery time and costs of the considered containers. The notations used to formulate the model are listed as follows:

Sets

I	Set of containers
P	Set of potential platoons

Parameters

Cod_n	Transportation cost of mode n between the port and the target zone
Cl	Labor cost for external trucks
Cp	Platoon formation cost
AN_n	Number of available vehicles of mode n
To	Initial start time of the loading process at the quay side
Tod_n	Transportation time of mode n between the port and target zone
TA_i	Lower bound of admissible delivery time for container i
TB_i	Upper bound of admissible delivery time for container i
U_B	Minimum number of admissible AGVs in a platoon
L_B	Maximum number of admissible AGVs in a platoon
$m_1 ... m_4$	Lower bounds of the left-hand side of the respective constraints
$M_1 ... M_5$	Upper bounds of the left-hand side of the respective constraints

Variables

Z_{in}	1: if container i is delivered by mode n 0: otherwise
V_{ip}	1: if the AGV carrying container i joins platoon p 0: otherwise
σ_p	1: if platoon p is formed 0: otherwise
δ_i	1: if DF_i is positive 0: otherwise
ST_{in}	Delivery time of container i by mode n
RT_{in}	Arrival time of the vehicle of mode n carrying container i at its destination
IT_{in}	Idle time of vehicle carrying container i of mode n
DF_i	Auxiliary variable which is used to define stacking time of container i
t_{4_i}	Stacking time of container i

Then, the proposed multi-objective optimization model is formulated as:

$$Min\, F_T = \sum_{i \in I} \Big(w_1(t_1 + t_2 + t_3 + t_5 + t_6) Z_{i1} + w_1(t'_1 + t'_2 + t'_3) Z_{i2} + w_2 t_{4_i} + w_3 \sum_{n=1,2} IT_{in} \Big) \quad (1)$$

$$Min\, F_C = \sum_{i \in I} \sum_{n=1,2} Cod_n\, Z_{in} + \sum_{i \in I} Cl\, Z_{i1} + \sum_{p \in P} Cp\, \sigma_p \quad (2)$$

$$\sum_{i\in I} Z_{in} \leqslant AN_n \qquad \forall n = 1,2 \tag{3}$$

$$\sum_{n=1,2} Z_{in} = 1 \qquad \forall i \in I \tag{4}$$

$$Z_{i2} = \sum_{p\in P} V_{ip} \qquad \forall i \in I \tag{5}$$

$$\sum_{i\in I} V_{ip} \leq U_B\,\sigma_p \qquad \forall p \in P \tag{6}$$

$$\sum_{i\in I} V_{ip} \geq L_B\,\sigma_p \qquad \forall p \in P \tag{7}$$

$$ST_{in} \geq (To + DT_{in} + Tod_n)Z_{in} \qquad \forall i \in I, n = 1,2 \tag{8}$$

$$DT_{i1} = t_1 + t_2 + t_3 + t_{4_i} + t_5 + t_6 \qquad \forall i \in I \tag{9}$$

$$IT_{in} = ST_{in} - (To + DT_{in} + Tod_n)Z_{in} \qquad \forall i \in I, n = 1,2 \tag{10}$$

$$DF_i = TA_i Z_{i1} - (To + t_1 + t_2 + t_3 + t_5 + t_6 + Tod_1) \qquad \forall i \in I \tag{11}$$

$$DF_i \leq M_1 \delta_i \qquad \forall i \in I \tag{12}$$

$$DF_i \geq m_1(1 - \delta_i) \qquad \forall i \in I \tag{13}$$

$$t_{4_i} = DF_i \delta_i \qquad \forall i \in I \tag{14}$$

$$TA_i Z_{in} \leq ST_{in} \leq TB_i Z_{in} \qquad \forall i \in I, n = 1,2 \tag{15}$$

$$Z_{in}, V_{ip}, \sigma_p, \delta_i \in \{0,1\} \qquad \forall i \in I, p \in P, n = 1,2 \tag{16}$$

$$ST_{in}, IT_{in}, t_{4_i} \geq 0 \qquad \forall i \in I, n = 1,2 \tag{17}$$

The objective function (1) minimizes dwell time including loading/unloading, travel within zone and stacking time as well as idle time of the vehicles of two modes (w_1, w_2 and w_3 capture the relative importance of time components). In the objective function (2) the total cost of the system involving transportation, labor and platoon formation costs are minimized. Labor cost is the wage paid to the drivers of the external trucks and platoon formation cost expresses the cost of assigning a human-driven leading vehicle and its driver to each string.

Constraint (3) ensures that the limits on the available numbers of AGVs and external trucks are respected. Constraint (4) guarantees that each container is delivered by one of the transportation modes. Constraint (5) implies that an AGV can leave the port only if it joins a platoon. Constraints (6) and (7) confine the number of vehicles in a platoon. Consistency of service time is guaranteed by constraint (8). Dwell time of first transportation mode is obtained by constraint (9). Constraint (10) specifies the idle time of the vehicles of each transportation mode. The stacking time of each container is obtained through constraints (11) to (14). The constraints imply that each container of mode 1 is stacked only if it would arrive sooner than its admissible service time in case of no stacking. This is distinguished by variable δ_i. Time windows are represented by constraint (15). Finally, constraints (16) and (17) imply the type of variables.

Constraints (8), (10) and (14) are non-linear. These are linearized to transform the model into a mixed-integer linear programming (MIP) formulation as follows:

$$ST_{in} - To - DT_{in} - Tod_n \geq m_2(1 - Z_{in}) \qquad \forall i \in I, n = 1,2 \qquad (18)$$

$$RT_{in} - To - DT_{in} - Tod_n \leq M_2(1 - Z_{in}) \qquad \forall i \in I, n = 1,2 \qquad (19)$$

$$RT_{in} - To - DT_{in} - Tod_n \geq m_3(1 - Z_{in}) \qquad \forall i \in I, n = 1,2 \qquad (20)$$

$$RT_{in} \leq M_3 Z_{in} \qquad \forall i \in I, n = 1,2 \qquad (21)$$

$$IT_{in} = ST_{in} - RT_{in} \qquad \forall i \in I, n = 1,2 \qquad (22)$$

$$t_{4_i} - DF_i \leq M_4(1 - \delta_i) \qquad \forall i \in I \qquad (23)$$

$$t_{4_i} - DF_i \geq m_4(1 - \delta_i) \qquad \forall i \in I \qquad (24)$$

$$t_{4_i} \leq M_5 \delta_i \qquad \forall i \in I \qquad (25)$$

Constraint (18) is a linearized version of constraint (8). Constraint (10) is linearized by constraints (19)–(22) and constraint (14) is linearized by constraints (23)–(25).

4 Solution Approach

In the proposed bi-objective model, it is impossible to obtain an individual solution that can simultaneously optimize both objective functions. For this reason, the augmented epsilon constraint method is used to achieve Pareto optimal solutions that capture the trade-offs between minimizing cost and time [14]. In this approach, we optimize one of the objective functions using the other as constraint accompanied by the original constraints of the problem. We take time (F_T) as the main objective function and calculate the range of F_C by creating the payoff table obtained by the lexicographic optimization of the objective functions. Then, the range of F_C is divided into k equal intervals resulting in $k+1$ grid points for F_C. Subsequently, $k+1$ optimization sub-problems are solved to obtain the Pareto front of the problem. The optimization sub-problem for the lth grid point is formulated as:

$$Min\, F_T - \varepsilon(\frac{S_l}{r}) \qquad (26)$$

s.t.

$$F_C + S_l = e_l \qquad (27)$$

Equations (3)–(7), (9), (11)–(13), (15)–(17), (18)–(25)

ε is a small number (10^{-6}–10^{-3}) and e_l is obtained as $e_l = ub - \frac{lr}{k}$ where ub and r are the upper bound and range of F_C, respectively.

In order to derive the best compromise solution from the obtained Pareto front, membership function in fuzzy sets is applied [18]. A linear membership function for each of the objective functions is introduced as:

$$\mu_m^l = \begin{cases} 0 & F_m^l \leq F_m^{\min} \\ \frac{F_m^{\max} - F_m^l}{F_m^{\max} - F_m^{\min}} & F_m^l \leq F_m^l \leq F_m^{\max} \\ 1 & F_m^l \geq F_m^{\max} \end{cases} \tag{28}$$

Where $m = T, C$ and l indicate the two objective functions and grid points, respectively. Then, the overall membership function is normalized as:

$$\mu^l = \frac{\varpi_1 \mu_1^l + \varpi_2 \mu_2^l}{\sum_{g=1}^{k+1} \sum_{m=1,2} \varpi_m \mu_m^g} \tag{29}$$

Where ϖ_m is the weight value of the mth objective function. Finally, the solution with the maximum membership function μ^l is selected as the best compromise solution.

5 Numerical Results

5.1 Experimental Settings

We consider container deliveries from the port of Rotterdam (western part of the seaport that is known as Maasvlakte area) to the logistic hub Venlo (Hutchison Ports Venlo) which is an important hinterland hub in Europe. This hub is located in the southeast of the Netherlands and within 200 km distance from the port of Rotterdam. The MIP model is coded in IBM ILOG CPLEX Optimization Studio 12.7 and due to its features, the model can be easily solved for large size instances in a reasonable time (namely 27.45 s for 1000 containers). Therefore, no heuristic solution approach was required. The experiments are carried out on a computer with Intel®Core i7-8650U CPU 1.9 GHz, 2.11 GHz, and 7.88 GB memory available.

To illustrate the features of the optimal solutions in details, it is considered that 50 containers can be directly delivered to their final destination. So, the remainder of the containers will follow the classic stacking procedure. As mentioned, scaling up does not impact the features of the problem and the model can be easily solved for larger sizes. We have taken 50 available AGVs as well as trucks to investigate optimal transportation modes for these containers. The planning horizon starts as the containers are unloaded off the ship. The destination time-windows for these containers can differ as their packed components may vary (Table 3):

Table 3. Destination time windows (in hours)

Containers	1–10	11–20	21–30	31–40	41–50
TA_i	3	3	4	4	4.5
TB_i	8	8	8	8	8

Distances are transformed into travel time by considering speeds of 75 km/h for trucks and 55 km/h for AGVs in the linking road of the origin to destination and 25 km/h for both modes within the container terminal of the port. Travel costs are proportional to distance and are higher for trucks due to higher fuel costs. Fuel cost reductions are observed when vehicles travel in a string which is due to lower air drag. The labor cost and platoon formation cost are 60 and 200 monetary units, respectively. The number of admissible AGVs in a platoon is confined to (2, 4).

5.2 Results

Optimizing the proposed model yields the following results (Table 4):

Table 4. Results

$F_1 = 22.316$	$Z_{1-50,1} = 0$	$IT_{1-40,2} = 0$	$\sigma_{1-13} = 1$
$F_2 = 11600$	$Z_{1-50,2} = 1$	$IT_{41-50,2} = 0.0767$	$\sigma_{14,15} = 0$

The results indicate that all the containers are delivered by AGVs. This not only shortens the dwell time of the containers by decreasing loading/unloading processes and eliminating stacking but also brings considerable cost savings.

The AGVs join 13 platoons to reach their destination and twelve of these platoons contain their maximum admissible AGVs in a string which is four in our problem. This is economically justifiable as it decreases the number of required platoons, hence platoon formation costs. Although using ordinary trucks for the remaining two containers is more economical than applying AGVs and forming a new platoon, these two containers are also delivered by AGVs joining the 13th platoon. That is because efficient time management is the top priority of the model which results in the application of AGVs.

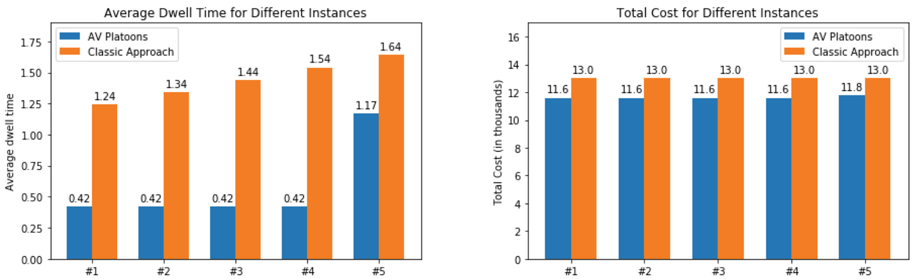
In order to deep dive into the features of our proposed model, it is essential to analyze the impact of time-windows on the optimal solutions. Table 5 provides optimal solutions obtained by varying TA_i, $\forall i = 41–50$.

By increasing TA_{41-50} up to 6.5, the idle time of the AGVs rises. That is because the vehicles need to wait longer for delivery time window to be open. The optimal transportation mode is still the same, hence the dwell time and total cost of the system undergo no changes. As TA_{41-50} reaches 7, it is not optimal to use AGVs anymore and trucks are applied instead. Accordingly, the dwell time and total cost increase. The containers wait 3.28 h in stack before leaving the port. These convey an important insight: As the delivery time window shifts later, direct delivery by AGVs loses its efficiency due to longer idle times at the destination.

Table 5. The impact of time windows on the optimal solutions

Instance	TA_{41-50}	F_1	F_2	$Z_{41-50,n}$		$IT_{41-50,n}$		$t_{4_{41-50}}$
				n = 1	n = 2	n = 1	n = 2	
#1	5	29.816	11600	0	1	0	0.577	0
#2	5.5	37.316	11600	0	1	0	1.077	0
#3	6	44.816	11600	0	1	0	1.577	0
#4	6.5	52.316	11600	0	1	0	2.077	0
#5	7	58.432	11800	1	0	0	0	3.28

The average dwell time of each container and total costs of the system for these five problem instances (as introduced in Table 5) in the classic and proposed approaches are illustrated in Fig. 2.



(a) Dwell Times (b) Total Costs

Fig. 2. Comparison of dwell time and costs in two approaches

As shown, the average dwell time of the containers decreases by applying AGVs in all the problem instances. This is highly important since dwell time is a significant performance measure for ports. Moreover, the stacking is eliminated in this setting which is extremely desirable due to space limits and high container traffics in the yard of container terminals.

As platoon formation cost increases, forming a platoon becomes less economical. In order to investigate whether this increase affects the optimal solutions of the problem and specifically the transportation mode, a sensitivity analysis on C_p is carried out and the results are provided in Table 6.

With 25% increase in C_p, the optimal transportation mode is still selected as AGVs for all 50 containers. So, F_1 undergoes no changes and 25% boost in platoon formation costs raises F_2 to 12250. As C_p is increased by 50–75%, the optimal mode for two containers changes from AGVs to trucks preventing the

Table 6. The impact of platoon formation cost on the optimal solutions

Instance	C_p	F_1	F_2	Containers	Z_{in}		IT_{in}		t_{4_i}
				i	n = 1	n = 2	n = 1	n = 2	
#6	250	22.316	12250	$\forall i = 1{-}50$	0	1	0	0.0767	0
#7	300	23.209	12740	$\forall i = 1{-}48$	0	1	0	0.0767	0
				$\forall i = 49, 50$	1	0	0	0	
#8	350	23.209	13340	$\forall i = 1{-}48$	0	1	0	0.0767	0
				$\forall i = 49, 50$	1	0	0	0	
#9	400	24.996	13820	$\forall i = 1{-}44$	0	1	0	0.0767	0
				$\forall i = 45{-}50$	1	0	0	0	

formation of 13th platoon. With further increase in C_p (100%), four more containers are delivered by trucks which decreases the number of required platoons to 11.

These results are compromised solutions in the Pareto front with the highest normalized membership value for the two objectives. Expressly, our approach takes into account possible solutions between optimizing either of the objective functions and selects the most promising one. As an instance, for $C_p = 400$, it is optimal to deliver all 50 containers by AGVs from the perspective of time (with $F_1 = 22.316$ and $F_2 = 14200$) and trucks are optimal for all 50 containers from cost view (with $F_1 = 56.9$ and $F_2 = 12500$). Then, with time as the first objective, the multi-objective approach suggests to use six trucks and 44 AGVs (with $F_1 = 24.97$ and $F_2 = 13820$).

Emission Analysis. Heavy duty vehicles are responsible for 27% of road transport CO_2 emission and European Commission is constantly proposing regulations on reducing CO_2 emissions from these vehicles. Accordingly, emissions should be captured in evaluation of any transportation setting. For heavy-duty vehicles, the UK Transport Research Laboratory has developed a function to estimate CO_2 emission of a travel [8]:

$$E = (\alpha_0 + \alpha_1 v + \alpha_2 v^2 + \alpha_3 v^3 + \frac{\alpha_4}{v} + \frac{\alpha_5}{v^2} + \frac{\alpha_6}{v^3})d \tag{30}$$

where α_0,...,α_6 are constant parameters for each vehicle type, v is the travel speed and d is the travel distance. For heavy-duty vehicles with gross weight 7.5–16 tones we have: $\alpha_0 = 871$, $\alpha_1 = -16$, $\alpha_2 = 0.143$, $\alpha_3 = \alpha_3 = \alpha_6 = 0$ and $\alpha_5 = 32031$. It should also be noted that platooning reduces fuel consumption due to reduction in air drag. This reduction is up to 9.7% for the following vehicles in the string that directly impacts emissions. Then, Eq. (30) should take into account this reduction for AGVs in a platoon. The total CO_2 emissions of the vehicles carrying 50 mentioned containers in the classic and proposed approach are obtained as 4810.69 and 3920.51 kg, respectively. This indicates that the proposed approach can bring 18% (890.17 kg) decrease in CO_2 emissions which is highly desirable. Then, the approach not only results in cost and time savings but also provides an environmentally friendlier setting.

6 Conclusions

Research on automated trucks and AVs has demonstrated the effectiveness of platooning to save fuel, costs, and emissions. Intelligent AGVs operated at ports may form platoons to establish an efficient and sustainable connection between port and hinterland, but models for these AGV platoons still need to be introduced and evaluated. In this work, we have proposed a multi-objective mixed-integer programming model for AGV platooning as a transfer mode between the port of Rotterdam and its hinterland. We have found that AGV platoons indeed offer a significant potential to reduce costs, dwell times, and emissions. In this way, our work transfers the platooning concept to port/hinterland operations and, by connecting two AGV-ready zones, it extends the work by Scherr et al. [16,17] who proposed platooning as a link between AV-ready areas in city logistics. In addition, the proposed multi-objective approach allows us to obtain Pareto optimal solutions, dealing with the trade-off between costs and time. Moreover, our emission analysis comparing conventional drayage trucks to port AGVs with air drag, provides detailed insight in the environmental impact of AGV platoons.

To the best of our knowledge, this is the first work to explore the potential of AGV platoons to connect ports with their hinterland, and our results provide first evidence for the advantages of this concept. In the long run, these findings may motivate further case studies and alternative concepts of AGV platoons in the port hinterland as well as gradual infrastructural investments that could allow us to scale up the approach. Nonetheless, while this study makes a first step, more research is needed to fully comprehend the potential of our approach and derive clear recommendations for policy makers to foster infrastructural adjustments. This research can be extended to a pickup-and-delivery structure where export containers may enter the port under a similar setting.

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