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# Proposal of a multi-agent model for the sustainable truck scheduling and containers grouping problem in a Road-Rail physical internet hub

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Physical Internet (PI) was introduced as a global standardised and interconnected logistics system based on PI-nodes, PI-movers and PI-containers as a mean toward global logistics sustainability. One important issue regarding PI-nodes concerns the planning and scheduling of operations and the management of PI-containers, both in a deterministic and a perturbed environment. This research considers the Road-Rail PI-hub sustainable truck scheduling and PI-containers grouping problem. In our research we consider the weighted sum of the number of used wagons, the internal distance travelled by PI-containers from PI-docks to wagons as well as the trucks' tardiness, which translate the search for sustainable logistics. In this paper, an effective and reactive multi-agent system based model (MAS) is developed for the resolution of the trucks scheduling and PI-containers grouping. To ensure the efficiency of the MAS and improve the quality of each of its solutions, three concurrent hybrid meta-heuristics are embedded within three parallel scheduling agents. Then, a mixed integer linear programming model (MILP) is proposed to evaluate the performance of the MAS. Finally, the MAS is also evaluated under internal perturbations. The obtained results show the ability of the MAS to provide alternative sustainable solutions by rescheduling trucks in case of disruptions.

**Keywords:** Road-Rail Physical Internet hub; MILP mathematical model; multi-agent system; perturbations; sustainability; scheduling

## 1. Introduction

As a novel Supply Chain Management (SCM) concept, Physical Internet (PI or  $\pi$ ) has recently attracted considerable interest of both the academic researchers and the industrial community (Treiblmaier, Mirkovski, and Lowry 2016; Pan et al. 2017). PI is introduced by Montreuil, Meller, and Ballot (2010) as a worldwide interconnected open logistics system aiming to change the way goods are handled, moved, stored and shipped based on the metaphor of the Digital Internet. The PI is based on the physical and digital inter-connectivity of the supply chain through the encapsulation of freight in modular PI-containers as data packets in the TCP-IP protocol. The aim of using standardised modular PI-containers is to reduce the energy consumption of resources and to improve the efficiency and resilience of the global supply chain (Montreuil 2011; Lin et al. 2014).

The main objective of the PI is to ensure the sustainability of the supply chain and logistics systems in three main aspects: economical, environmental and social (Montreuil 2011; Meller et al. 2012). There are three key elements which are necessary to exploit the PI in Road-Rail problems: PI-containers, PI-movers and PI-nodes. The PI-containers are standardised containers and they can be handled and stored by different companies. The PI-movers are used to move and handle the PI-containers such as PI-vehicles (PI-trucks, PI-left, etc.) and PI-carriers (PI-wagons, PI-trailers, etc.). The PI-nodes are locations for receiving, storing and transferring PI-containers between PI-movers. The PI-nodes can be PI-transits, PI-switches, PI-bridges or PI-hubs such as Road-Road based cross-docks and Road-Rail based cross-docks (Montreuil, Meller, and Ballot 2010; Sarraj et al. 2014). One important issue regarding PI-nodes concerns the planning and scheduling of operations and the management of PI-containers, both in a deterministic and a perturbed environment. This paper focuses on a specific type of PI-node that is PI-hub, and more precisely, Road-Rail PI-hub (Figure 1). In this context, we consider the truck scheduling and containers assignment and grouping in the Road-Rail section of the PI-hub, which is used to transfer PI-containers from the trucks to the trains' wagons.

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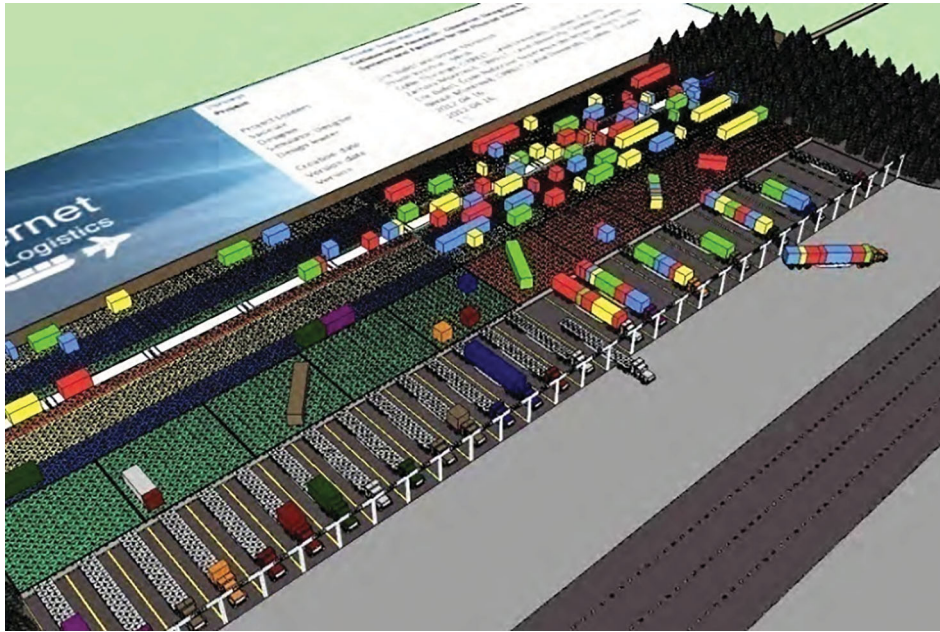


Figure 1. Layout of the Physical Internet Road-Rail PI-hub (Ballot, Montreuil, and Thivierge 2012).

The efficiency of the PI concept in the global supply chain has been demonstrated in the literature via different applications using different approaches (Pan et al. 2019). Through a literature review in Section 2, it will be shown that several limits can be found especially on the works related to cross-dock scheduling in the PI context. Most of the studies tend to focus only on the global supply chain network optimisation instead of optimising local operations related to the cross-docking or production. The focus of our contribution is centred on the optimisation of the operations occurring in the PI-nodes and more specifically the Road-Rail PI-hub. The problem considered in this paper relates to truck scheduling and PI-containers grouping. The scheduling problem consists in assigning the trucks to the docks on a time horizon, while the PI-containers' assignment and grouping are performed by loading the PI-containers into the wagons while respecting the capacity and destinations constraints of the wagons. In this paper, we try to fill the gap in the literature by proposing a multi-agent model to solve this problem. A MILP formulation is proposed to model the problem and to evaluate the performances of the multi-agent system in a static context. The multi-agent system is also evaluated in a dynamic environment.

The remaining of this paper is structured as follows: In Section 2, the literature related to Physical Internet and especially to Road-Rail PI-hub is reviewed. The description of the studied problem is then detailed in Section 3. The proposed MILP model and multi agent model for the Road-Rail PI-hub scheduling and grouping problem are detailed in Section 4. The results analysis for the MAS and MILP is presented in Section 5. Then, the MAS under perturbations is presented in Section 6. Finally, a conclusion and future research directions are discussed.

## 2. Literature review

For the past few years, as the literature of PI is steadily growing, many researchers contributed to the PI using different methodologies such as quantitative modelling, case studies and simulations. Several authors studied the design and dimensions of the PI-containers (Lin et al. 2014; Gazzard and Montreuil 2015; Landschützer, Ehrentraut, and Jodin 2015). The hyperconnectivity of the supply chain in PI context was addressed by many authors in the literature. Crainic and Montreuil (2016) introduced the idea of hyperconnected city logistics and its main concepts. Sohrabi (2016) presented optimisation models for hyperconnected distribution systems while other studies such as in Marcotte, Montreuil, and Coelho (2015) focused on production operations. Pan et al. (2015), Naccache (2016) and Yang (2016) addressed inventory control and management in hyperconnected supply chain, while other studies are more focused on the design of PI facilities such as Road-based cross-docking hubs (Montreuil et al. 2013) and Road-Rail PI-hubs (Ballot, Montreuil, and Thivierge 2012). Qiao, Pan, and Ballot (2019) developed a multi-periods dynamic pricing model to study the influence of future requests on the current pricing decision. A detailed classification and review of the PI related works could be found in Treiblmaier, Mirkovski, and Lowry (2016) and Pan et al. (2017). Multimodality in transportation, which is a cornerstone in the PI network, consists of using at least two different modes of transportation. As an extension of the intermodal transportation, the

sychromodal freight transportation was introduced as a new concept that, in addition to multimodality, considers real time reactive approaches that can handle possible disruptions in the supply chain such as delays and re-routing of the trucks (Ambra, Caris, and Macharis 2019).

In classical supply chain networks, the storage and distribution are often restricted and fixed and the architecture of the network is usually hierarchical. On the contrary, the PI uses decentralised approaches that ensure synchronisation and interconnectivity of the supply chain. Indeed, in the PI, the storage and transportation resources are shared and can be used on the request of the user which can be a supplier, a hub or a retailer. This flexibility of the network has shown to outperform the classical one in the inventory problem (Yang, Pan, and Ballot 2017a) even in case of disruptions (Yang, Pan, and Ballot 2017b). The positive impact of PI configuration was also observed from social and environmental aspects (Fazili et al. 2017).

In the last two decades, improving the sustainability of the supply chain is increasingly becoming a priority goal for logistics companies to consider the environmental, economic and social aspects while reducing total costs and optimising the overall supply chain operations. The sustainability of a supply chain is addressed through the interactions between the different components of the supply chain to generate environmental, economic and social gains for a single component or the whole supply chain (Taylor and Vachon 2018). Recently, many reviews have been done concerning the sustainability of supply chains. The existing literature has been limited to individual aspects of supply chain sustainability instead of addressing global integrated dimensions which should consider other aspects such as the social and economic dimensions and the green supply chain management (Winter and Knemeyer 2013). The internal and external constructs of supply chain have an important impact on the sustainability performance. The internal supply chain practices have a major effect on the environmental sustainability. The external coordination and communication of supply chain have a direct impact on the sustainability not only from the environmental view but also from the social aspect (Jadhav, Orr, and Malik 2018). A recent literature review on this topic (Koberg and Longoni 2018) found that the configuration of the supply chain members and the relational mechanisms are the key-elements towards the sustainability in the global supply chain. The first element, which is the configuration, consists of the structural arrangement and linkage between the different actors of the supply chain network. The relational mechanism describes the relationships management of the supply chain actors.

In the context of sustainability, many papers addressed the supply chain resilience to different kinds of perturbations. In order to examine the resilience and robustness of a supply chain, different approaches such as simulation-based studies and mathematical programming can be used. Many studies that used simulation to examine sustainability and resilience can be found. For example, Ivanov (2018) analysed the effect of disruption propagation in supply chain through discrete event simulation aiming at reducing the ripple effect while enhancing the sustainability. Several sustainability factors such as the single sourcing strategy or reduction of storage have different impacts on both ripple effect and sustainability. Yang, Pan, and Ballot (2017a) proposed a vendor-managed inventory model and developed a simulation-based optimisation model to handle inventory control decisions. The authors compared the performance of the classical hierarchical inventory model and the PI-enabled model. Their results show that the PI inventory model outperforms the classical models thanks to its flexibility and its ability to dynamically share inventory and transportation resources between hubs. Using a simulation model, Yang, Pan, and Ballot (2017b) examined the robustness of inventory models in PI interconnected network. The authors found that the PI model performs better than the classical model in case of perturbations in hubs and plants. Fazili et al. (2017) compared the performance of PI to a conventional logistics system using a Monte-Carlo Simulation. Their results show that, from a social point of view, the PI decreases the driving time and, from an environmental point of view, it reduces the travel distance and the truck traffic. Other researchers used stochastic programming to address the sustainability issue. For instance, Jabbarzadeh, Fahimnia, and Sabouhi (2018) used a two-phase approach which consists on combining a c-means fuzzy clustering method to assess sustainability and a stochastic programming model to maintain supply chain sustainability performance in case of random disruptions.

As stated in the introduction, this research contributes to the operations planning of the Road-Rail PI-hub Cross-dock, which is designed to transfer PI-containers from trains to other trains, from trucks to trains and from trains to trucks. In addition to temporary storage zones, the Road-Rail PI-hubs are composed of three main PI-sorters: Rail-Road PI-sorters to transfer the PI-containers from the wagons (or railcars) to the trucks, Road-Rail PI-sorters which are used for transferring the PI-containers from the trucks to the wagons and Rail-Rail PI-sorters to transfer the PI-containers between the trains. The Rail-Road PI-hub was addressed in the literature by many researchers; for instance, a functional design for the Road-Rail PI-hub was suggested by Ballot, Montreuil, and Thivierge (2012). Their paper describes the flow of the PI-containers, the trucks and the trains in the Road-Rail PI-hub. Furthermore, they also provided several Key Performance Indicators (KPIs) to evaluate the performance of the Road-Rail PI-hub from the customers' perspective on the one hand (such as: the processing time of trains, the empty places on trains and trucks, . . .) and from the Road-Rail PI-hub operators' perspective on the other hand (for example: the number of wagons, number of gates, number of PI-containers handled per period, . . .). Other studies focused more on the grouping of PI-containers in the Rail-Road PI-hubs; for example, Pach et al. (2014)

Table 1. Summary of the Road-Rail PI-hub related works.

Authors	Research work	Solution methods
Ballot, Montreuil, and Thivierge (2012)	Functional design and KPIs for the Road-Rail PI-hub	Conceptual and functional design
Chargui et al. (2019)	Sustainable multi-objective truck scheduling for Rail-Road PI-hub	Multi-objective MIP and hybrid meta-heuristics
Pach et al. (2014)	Grouping strategies of PI-containers and their impact on truck loading	Multi-agent simulation
Sallez et al. (2015)	Hybrid control architecture for the routing of PI-containers	Multi-agent simulation
Sallez et al. (2016)	PI-containers' activeness applied to a case study in a Rail-Road PI-hub	Multi-agent simulation
Sun et al. (2018)	Rail-Road intermodal transport network	Multi-agent simulation
Vo et al. (2018)	ORCA hybrid architecture for the Rail-Road PI-hub	Multi-agent simulation
Walha et al. (2014)	Allocation of PI-containers to docks and trucks to docks in a Rail-Road PI-hub	MILP mathematical formulation, Heuristic
Walha et al. (2016)	Active and reactive approach for the Rail-Road allocation problem	Heuristic, Simulated Annealing, Multi-agent reactive approach

proposed different grouping strategies for loading PI-containers in the trucks. Their study showed the effect of the grouping of PI-containers on minimising the evacuation time in the Road-Rail PI-hub. Moreover, they also specified which strategy to use in each situation to avoid blocking the PI-docks which leads to truck loading delays. Sallez et al. (2016) studied the notion of activeness of PI-containers, which are considered as autonomous products that are able to communicate, learn and identify their state. The concept of PI-container activeness was evaluated through a simulation study on a Rail-Road PI-hub. Hybrid control architecture in Rail-Road PI-hub has been addressed by several authors in the literature. In a multi-agent simulation study, Sallez et al. (2015) developed a reactive approach in a hybrid control architecture for the routing of PI-containers in the Rail-Road PI-hub cross-dock. The robustness of their proposed reactive approach was evaluated by the average evacuation time of the PI-containers while considering possible internal and external perturbations. Vo et al. (2018) proposed an ORCA (Optimised and Reactive Control Architecture) hybrid architecture for the Rail-Road PI-hub. The performance of their approach was evaluated through a simulation study in which they compare different routing strategies. In order to highlight the environmental benefits of the PI, Sun et al. (2018) studied the Rail-Road intermodal transport network through an agent-based simulation and showed its impact on reducing fuel consumption. Several authors addressed the Rail-Road PI-hub allocation problem, which considers the train unloading section of the PI-hub that is used to transfer PI-containers from wagons to trucks. Walha et al. (2014) suggested a mathematical formulation and a heuristic to find the best assignment of the trucks to the docks while minimising the internal distance covered by the PI-containers from the wagons to the trucks. More recently, the same authors (Walha et al. 2016) developed a simulated annealing meta-heuristic for solving the Rail-Road allocation problem to minimise the distance travelled by the PI-containers and the number of used trucks. They also proposed a multi-agent based approach, which generates solutions while considering the dynamic aspect that takes into consideration the filling rate and the travelled distance. From a multi-objective perspective, Chargui et al. (2019) addressed the sustainability in the Rail-Road section by minimising the energy consumption of PI-conveyors and the outbound trucks cost using lexicographic goal programming. The problem was formulated as a multi-objective MIP model and then solved using two hybrid meta-heuristics. Table 1 summarises the research works that are the most related to the Road-Rail PI-hub.

In this paper, a multi-agent system based model is proposed for the scheduling of trucks as well as the assignment and grouping of PI-containers in the Road-Rail PI-hub. A multi-agent approach was adopted for several reasons. First, it enables to integrate highly reactive interaction mechanisms, which may be useful in a perturbed environment. Second, it can mirror some parts of the reality, namely the conflicting situations between the different stakeholders in charge of logistics aspects in the PI. Meanwhile, some attention must be paid to ensure the quality of the results obtained. For that purpose, the proposed MAS uses three parallel Scheduling Agents, each of them runs a different hybrid meta-heuristic: Variable Neighbourhood Search, Greedy Randomised Adaptive Search Procedure and Tabu Search; all those three meta-heuristics are hybridised with Simulated Annealing (VNS-SA, GRASP-SA and TS-SA). A mathematical model (MILP) for the Road-Rail PI-hub truck scheduling and containers' assignment and grouping problem is proposed to test the quality of the solutions provided by the MAS.

As introduced, one of the primary goals of the PI is to improve the sustainability of the global supply chain environmentally, socially and economically. The models proposed in this work (MAS and MILP) address sustainability through the minimisation of the number of wagons used as well as the reduction of the distance travelled by the PI-containers in the Road-Rail PI-sorter zone, which will reduce the electrical energy used by the PI-conveyors to transfer the PI-containers in addition to the reduction of the delay for the trucks to unload. The proposed models address two of the three pillars of the sustainable development, namely the economic and environmental pillars. The PI approach considers the social pillar as an important one, especially the health of truck drivers who spend most of their time on the road (Montreuil 2011). In this paper, from an economic point of view, the proposed models reduce the total cost by using a minimum number of wagons and the delay of the trucks which can result in financial penalties from the transportation providers. From an environmental point of view, in addition to reducing the distance travelled by PI-containers which leads to minimising the energy used by the PI-conveyors, the two models minimise the number of used wagons which reduces the emission of CO<sub>2</sub> by the train's locomotive. In the two models, the main constraint is that the PI-containers with the same destination must be loaded and grouped in consecutive wagons while minimising the objective function. The objective is the grouping of PI-containers while keeping the ones with the same destination in consecutive wagons. The two proposed models are then evaluated on the same instances. Finally, in order to consider dynamic aspects, the MAS is evaluated facing internal perturbations in the PI-hub.

### 3. Problem statement and assumptions

As introduced, in this paper, we consider the Road-Rail PI-hub truck scheduling and containers' assignment and grouping problem. As shown in Figure 2, in addition to the Rail-Rail section, the Road-Rail PI-hub is composed of two main sections: the Rail-Road section and the Road-Rail section.

In their paper, Walha et al. (2014) studied the allocation of the PI-containers to the Rail-Road section (Section 1 in Figure 2), where the PI-containers are unloaded from the wagons and transferred through the PI-Sorter and then loaded into the outgoing trucks.

Our research focuses on the second section of the Road-Rail PI-hub (Section 2 in Figure 2) which deals with the transfer of the PI-containers from the trucks to the wagons. The train is composed of many empty wagons. Each set of five wagons is considered as a single block. The wagons will be loaded with the PI-containers that are unloaded from the trucks.

Once the train enters the Road-Rail PI-hub, the first block of five wagons is assigned to the Rail-Road PI-sorter section. This step is out of the scope of this paper. This section is dedicated to the receiving of PI-containers from the train and loading them into the outgoing trucks. In the next step, the block of five wagons moves to the Road-Rail section to load PI-containers from the trucks. PI-containers with the same destinations must be loaded in the same consecutive wagons so that in the next visited Rail-Road PI-hub the unloading of the PI-containers and the scheduling of the outgoing trucks at the docks become easier. Once the first block of wagons is filled with PI-containers, the next block is assigned to the unloading Rail-Road section.

The main assumptions considered in this paper for the studied problem are the following:

- Inbound trucks can unload PI-containers with different lengths, and each of those PI-containers has a specific destination.

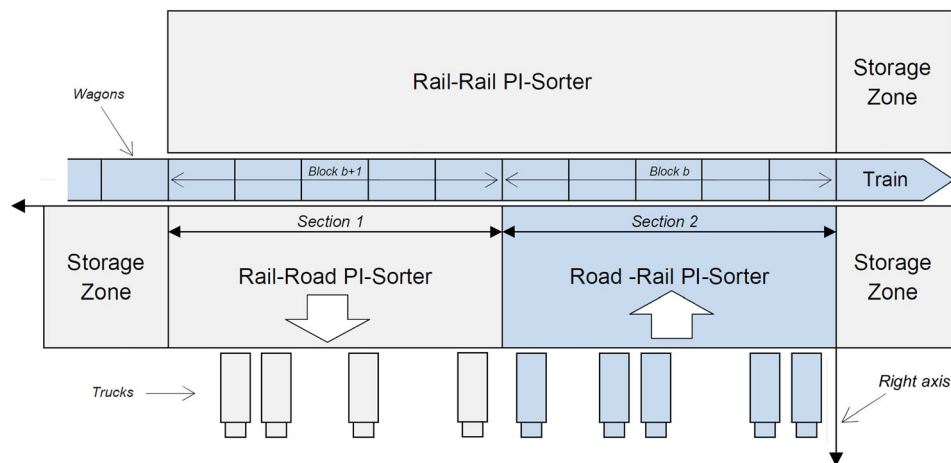


Figure 2. Overview of the Road-Rail PI-hub Layout (Inspired from Ballot, Montreuil, and Thivierge 2012).

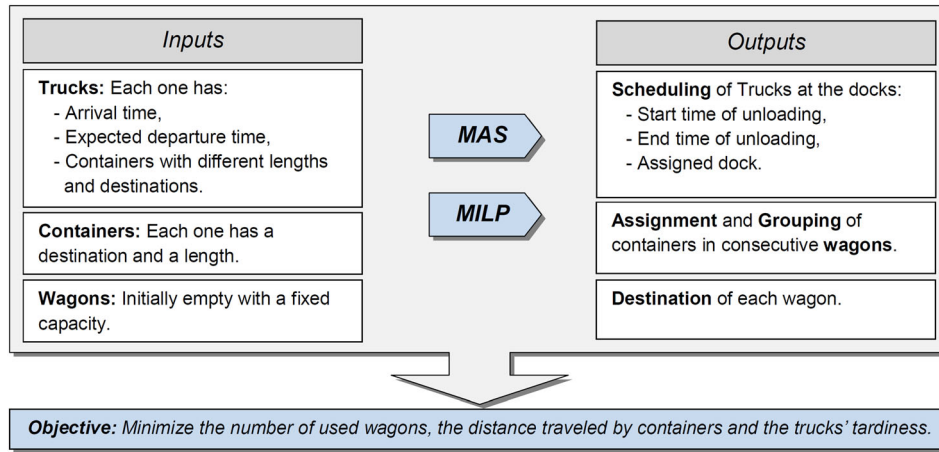


Figure 3. The main input and output data of the proposed models (MAS and MILP).

- PI-containers with the same destination must be loaded in consecutive wagons.
- Each of the train's wagons must load only PI-containers that have the same destination.
- There must be no empty wagon between two used wagons.

#### 4. Proposed models

In order to solve the studied problem, we propose a multi-agent system model (MAS) for which the objective is to minimise the number of used wagons, the distance travelled by the PI-containers from the trucks to the train's wagons as well as the tardiness of the trucks at the docks while respecting several constraints related to the wagons' capacity and the PI-containers' destinations. In order to assess the quality of the solutions provided by the MAS, a mathematical model is proposed by formulating the studied problem as a MILP model. Figure 3 shows the main inputs and outputs of the proposed models. It is important to mention that solving the studied problem using the MILP is not practical due to the computational times which are very high especially for large instances, and using the MILP in a reactive context is hardly feasible.

##### 4.1. Mathematical formulation

This section presents the proposed mathematical formulation of the Road-Rail scheduling and grouping problem as a mixed integer linear programming model (MILP). This model is an improved version of the MILP model proposed by Chargui et al. (2018) for the assignment problem in which the authors did not consider the time dimension. The problem consists of  $N$  PI-containers with different lengths  $L_i$  which are initially in  $H$  inbound trucks. A truck can unload PI-containers with different destinations among the  $D$  destinations considered in the model. Each truck must be scheduled at one of the  $K$  docks in the Road-Rail section for unloading. The unloaded PI-containers must be grouped in a set of minimum possible consecutive wagons from the total available wagons  $W$ . The trucks must be scheduled at the docks in order to minimise the total tardiness and the total distance travelled by the PI-containers from the docks to the wagons.

The proposed mathematical model has two main decisions for the Road-Rail problem:

- The scheduling of the trucks at the docks;
- The grouping and assignment of the PI-containers to the wagons.

The notations for input parameters, binary and continuous variables used in this paper are the following:

##### 4.1.1. Input parameters:

$N$	Total number of PI-containers
$K$	Number of docks
$D$	Number of destinations
$W$	Total number of wagons in the train

$H$	Number of trucks
$Q$	Wagon's capacity (useful length)
$i$	Indices of the PI-containers
$k$	Indices of the docks
$d$	Indices of the destinations
$w, w_1, w_2$	Indices of the wagons
$h$	Indices of the trucks
$E_h$	Arrival time of truck $h$
$F_h$	Expected departure time of truck $h$
$J_h$	Processing time of truck $h$
$V$	Changeover time of trucks
$P_k$	Position of the centre of the dock $k$ starting from the right axis of the Road-Rail PI-sorter zone
$R_w$	Position of the centre of the wagon $w$ starting from the right axis of the Road-Rail PI-sorter zone
$L_i$	Length of PI-container $i$

$$A_{hi} = \begin{cases} 1, & \text{if the PI – container } i \text{ is in the truck } h \\ 0, & \text{Otherwise} \end{cases}$$

$$S_{di} = \begin{cases} 1, & \text{if } d \text{ is the destination of the container } i \\ 0, & \text{Otherwise} \end{cases}$$

$\alpha$	Weighting factor for the number of used wagons
$\beta$	Weighting factor for the total distance travelled by PI-containers
$\gamma$	Weighting factor for the trucks' tardiness
$M$	A big positive number used to handle several constraints in the MILP (constraints 8, 9, 11 and 16). $M \geq \max(W, 5 * Wagon\_Length, Planning\_Horizon)$ .

#### 4.1.2. Decision variables

Binary variables:

$$x_{iw} = \begin{cases} 1, & \text{if the PI – container } i \text{ is assigned to the wagon } w \\ 0, & \text{Otherwise} \end{cases}$$

$$y_{hk} = \begin{cases} 1, & \text{if the truck } h \text{ is assigned to the dock } k \\ 0, & \text{Otherwise} \end{cases}$$

$$u_w = \begin{cases} 1, & \text{if the wagon } w \text{ is used} \\ 0, & \text{Otherwise} \end{cases}$$

$$e_{wd} = \begin{cases} 1, & \text{if } d \text{ is the destination of the wagon } w \\ 0, & \text{Otherwise} \end{cases}$$

$$g_{h_1 h_2} = \begin{cases} 1, & \text{if trucks } h_1 \text{ and } h_2 \text{ are assigned to the same dock} \\ & \text{and } h_1 \text{ is a predecessor of } h_2 \\ 0, & \text{Otherwise} \end{cases}$$

Continuous variables:

$r_h$	Start time of unloading truck $h$
$s_h$	End time of unloading truck $h$
$f_h$	Tardiness of truck $h$
$d_{iw}$	Distance travelled by the PI-container $i$ to the wagon $w$



#### 4.1.3. Objective function

The objective of the MILP model is to minimise the weighted sum of the number of used wagons, the total internal distance travelled by the PI-containers and the total tardiness of trucks.

$$\text{Minimize : } \alpha \sum_{w=1}^W u_w + \beta \sum_{i=1}^N \sum_{w=1}^W d_{iw} + \gamma \sum_{h=1}^H f_h \quad (1)$$

Where  $\alpha$ ,  $\beta$  and  $\gamma$  are the weighting factors for the number of used wagons, the total distance travelled by PI-containers and the total tardiness of trucks respectively ( $\alpha + \beta + \gamma = 1$ ). It is important to mention that those three objectives have three different units. The tardiness is expressed in minute, the distance in metre while the first objective is calculated as a non-dimensional number. Also, the values of the weighting factors  $\alpha$ ,  $\beta$  and  $\gamma$  can be set by the user or the decision maker depending on the priority and importance of each objective.

#### 4.1.4. Constraints

Table 2 presents the constraints of the MILP model with a description of each one in the last column.

In both constraints (8) and (9)  $w_1$  and  $w_2$  are used as indices and their value goes from 1 to  $W$ . The idea is to limit the difference between indices (absolute value) in order to keep all the used wagons consecutive in constraint (8) and to keep wagons with the same destinations consecutive in constraint (9).

The minimum value of the parameter  $M$  is:

$$M \geq \max(W, 5 * \text{Wagon\_Length}, \text{Planning\_Horizon})$$

Where  $W$  is the total number of wagons in the train, and  $5 * \text{Wagon\_Length}$  is the length of the Road-Rail section which can handle 5 wagons at a time (in this study,  $\text{Wagon\_Length} = 20$  m is the total length of one wagon and the useful length of the wagon is 18m). Indeed, in constraints (8) and (9) the minimum value of  $M$  is the total number of the wagons  $W$ . However, in constraint (11) the minimum value of  $M$  is the total length of the five wagons (length of the Road-Rail section). In constraint (16) the minimum value of  $M$  is the planning horizon of the instance. It is important to mention that the same length unit (which the metre ‘m’ in this study) must be used in all the length parameters ( $P_k$ ,  $R_w$ ,  $L_i$  and  $Q$ ) and the distance variable ( $d_{iw}$ ).

## 4.2. Multi-agent model

In this section, we present a detailed description of the architecture and the components of the MAS. Figure 5 illustrates the different components of the MAS. There are  $H$  Trucks Agents, a Train Agent, a Synchroniser Agent and three parallel Scheduling Agents (VNS-SA, GRASP-SA and TS-SA). The sequence diagram in Figure 6 summarises the communication and negotiation between the different agents of the proposed MAS which communicate in the following steps:

**Step 1:** The Trucks Agents send their arrival and expected departure time and the PI-containers’ destinations and lengths to the Synchroniser Agent.

**Step 2:** The Train Agent sends its wagons’ availability to the Synchroniser Agent.

**Step 3:** The Synchroniser Agent runs the Construction Heuristic (CH) to find an initial solution  $S_{INITIAL}$ .

**Step 4:** The Synchroniser Agent broadcasts the initial solution  $S_{INITIAL}$  to the three hybrid parallel Scheduling Agents.

**Step 5:** Each of the three Scheduling Agents runs a different hybrid meta-heuristic to improve the initial solution.

**Step 6:** The best solution  $S_{BEST}$  found by the three Scheduling Agents is sent to the Synchroniser Agent.

**Step 7:** The Synchroniser Agent broadcasts the schedule (start/end time of unloading and the assigned dock) to the Trucks Agents and the PI-containers grouping and wagons’ destinations to the Train Agent.

The MAS is composed of the following agents communicating with each other:

#### 4.2.1. Truck Agent

Before their scheduling at the docks, the Trucks Agents send the destination and the length of their PI-containers and their arrival and expected departure time to the Synchroniser Agent and wait for their schedule at the docks.

Table 2. Constraints of the MILP model.

#	Constraints	Descriptions
(2)	$\sum_{w=1}^W x_{iw} = 1 \quad (\forall i = 1 \dots N)$	Each PI-container $i$ unloaded from the truck $h$ must be assigned to only one wagon $w$ .
(3)	$\sum_{i=1}^N x_{iw} L_i \leq Q \quad (\forall w = 1 \dots W)$	The wagons' capacity $Q$ should not be exceeded by the total length of the assigned PI-containers.
(4)	$x_{iw} + x_{jw} \leq \sum_{d=1}^D S_{di} S_{dj} + 1$ $(\forall i, j = 1 \dots N, \forall w = 1 \dots W, i \neq j)$	Two PI-containers $i$ and $j$ with different destinations cannot be loaded in the same wagon.
(5)	$x_{iw} \leq u_w \quad (\forall i = 1 \dots N, \forall w = 1 \dots W)$	If a PI-container is assigned to a wagon, this wagon should be used ( $u_w = 1$ ).
(6)	$e_{wd} \leq S_{di} + 1 - x_{iw}$ $(\forall i = 1 \dots N, \forall w = 1 \dots W, \forall d = 1 \dots D)$	This constraint sets the destination for a wagon if there is any PI-container assigned to it.
(7)	$u_w = \sum_{d=1}^D e_{wd} \quad (\forall w = 1 \dots W)$	If a wagon is used, then, a destination must be assigned to that wagon.
(8)	$ w_1 - w_2  + 1 \leq \sum_{w=1}^W e_{wd} + M(2 - (e_{w_1d} + e_{w_2d}))$ $(\forall d = 1 \dots D, \forall w_1, w_2 = 1 \dots W, w_1 \neq w_2)$	The wagons which have the same destination must be consecutive.
(9)	$ w_1 - w_2  + 1 \leq \sum_{w=1}^W u_w + M(2 - (u_{w_1} + u_{w_2}))$ $(\forall w_1, w_2 = 1 \dots W, w_1 \neq w_2)$	All the used wagons must be consecutive in order to avoid empty wagons between the used ones (Figure 4).
(10)	$u_1 = 1$	The wagons are used starting from the first wagon.
(11)	$d_{iw} \geq  P_k - R_w  - M(2 - (A_{hi} * y_{hk} + x_{iw}))$ $(\forall i = 1 \dots N,$ $\forall w = 1 \dots W, \forall k = 1 \dots K, \forall h = 1 \dots H)$	The distance travelled by a PI-container from the dock to the wagon.
(12)	$\sum_{k=1}^K y_{hk} = 1 \quad (\forall h = 1 \dots H)$	Each one of the trucks must be assigned to only one dock.
(13)	$y_{h1k} + y_{h2k} - 1 \leq g_{h1h2} + g_{h2h1}$ $(\forall k = 1 \dots K, \forall h1, h2 = 1 \dots H, h1 \neq h2)$	These two constraints (13 and 14) handle the assignment and the sequencing of the trucks at the docks.
(14)	$g_{h1h2} + g_{h2h1} \leq 1 \quad (\forall h1, h2 = 1 \dots H)$	
(15)	$r_h \geq E_h \quad (\forall h = 1 \dots H)$	Each truck starts unloading the PI-containers after arriving to the PI-hub.
(16)	$r_{h2} \geq s_{h1} + V - M(1 - g_{h1h2})$ $(\forall h1, h2 = 1 \dots H)$	If the truck $h_1$ precedes the truck $h_2$ at the same dock, then $h_2$ starts the unloading after the end of unloading of the truck $h_1$ .
(17)	$s_h \geq r_h + J_h \quad (\forall h = 1 \dots H)$	This constraint calculates the end time of unloading a truck.
(18)	$f_h \geq s_h - F_h \quad (\forall h = 1 \dots H)$	This constraint calculates the tardiness of a truck.
(19)	$x_{iw}, y_{hk}, u_w, e_{wd}, g_{h1h2} \in \{0, 1\}$ $(\forall i = 1 \dots N, \forall w = 1 \dots W, \forall k = 1 \dots K,$ $\forall h, h1, h2 = 1 \dots H, \forall d = 1 \dots D)$	This constraint ensures that the variables are binary.
(20)	$r_h, s_h, f_h, d_{iw} \geq 0$ $(\forall i = 1 \dots N, \forall w = 1 \dots W, \forall h = 1 \dots H)$	This constraint ensures the positivity of the continuous variables.

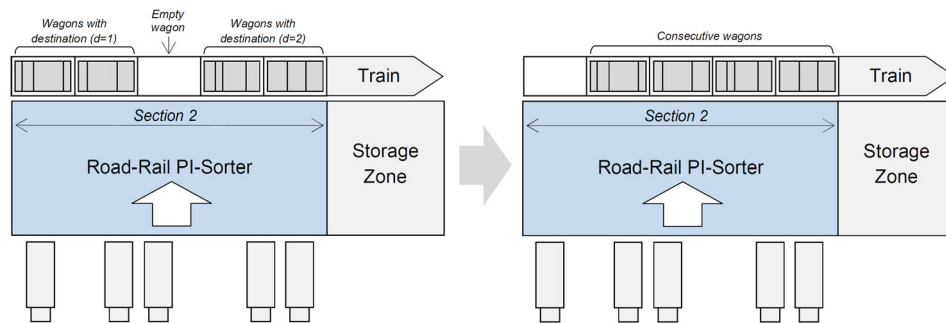


Figure 4. All the used wagons must be consecutive.

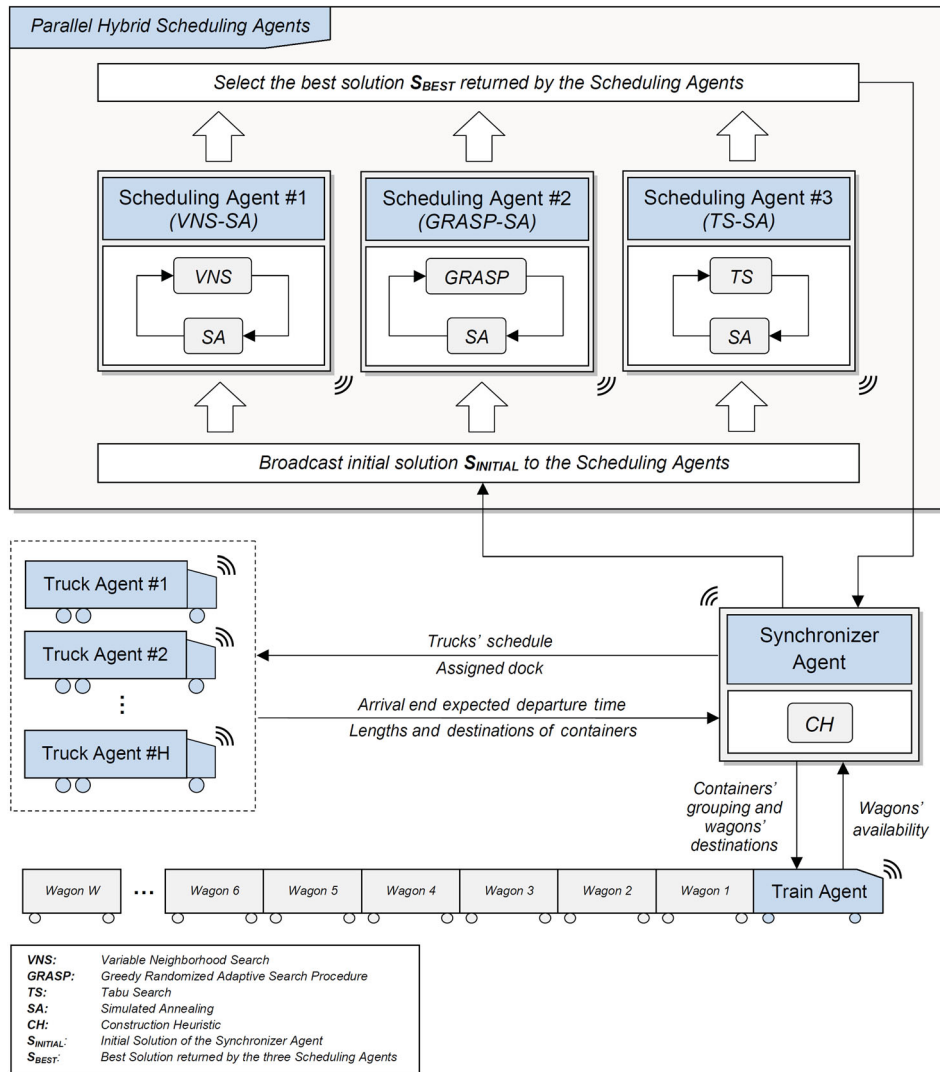


Figure 5. Architecture of the proposed MAS.

#### 4.2.2. Train Agent

The Train Agent sends the number of its available wagons and their capacities to the Synchroniser Agent and waits for the PI-containers to be grouped in the wagons.

#### 4.2.3. Synchroniser Agent

The aim of the Synchroniser Agent is to receive the requests from the Trucks Agents and the availability of wagons from the Train Agent, then, it runs a construction heuristic (CH) to find an initial grouping of PI-containers inside the wagons and also to find an initial scheduling of the trucks at the docks. Then, this initial solution is broadcasted to the three Scheduling Agents in order to improve it. A description of the CH pseudo code is presented in Algorithm 1.

As shown in Algorithm 1, in the first step, the Synchroniser Agent starts by sorting all the PI-containers in a decreasing order of their length and grouping them by destination. The objective is to use the fewest number of wagons. It is supposed that there is a sufficient number of available wagons in the train. Then, it finds the average position  $AvPos[h]$  of the truck using the position of its PI-containers in wagons. For each truck, the algorithm assigns the truck to the closest available dock to its average position  $AvPos[h]$  and assigns the start/end time for unloading the truck.

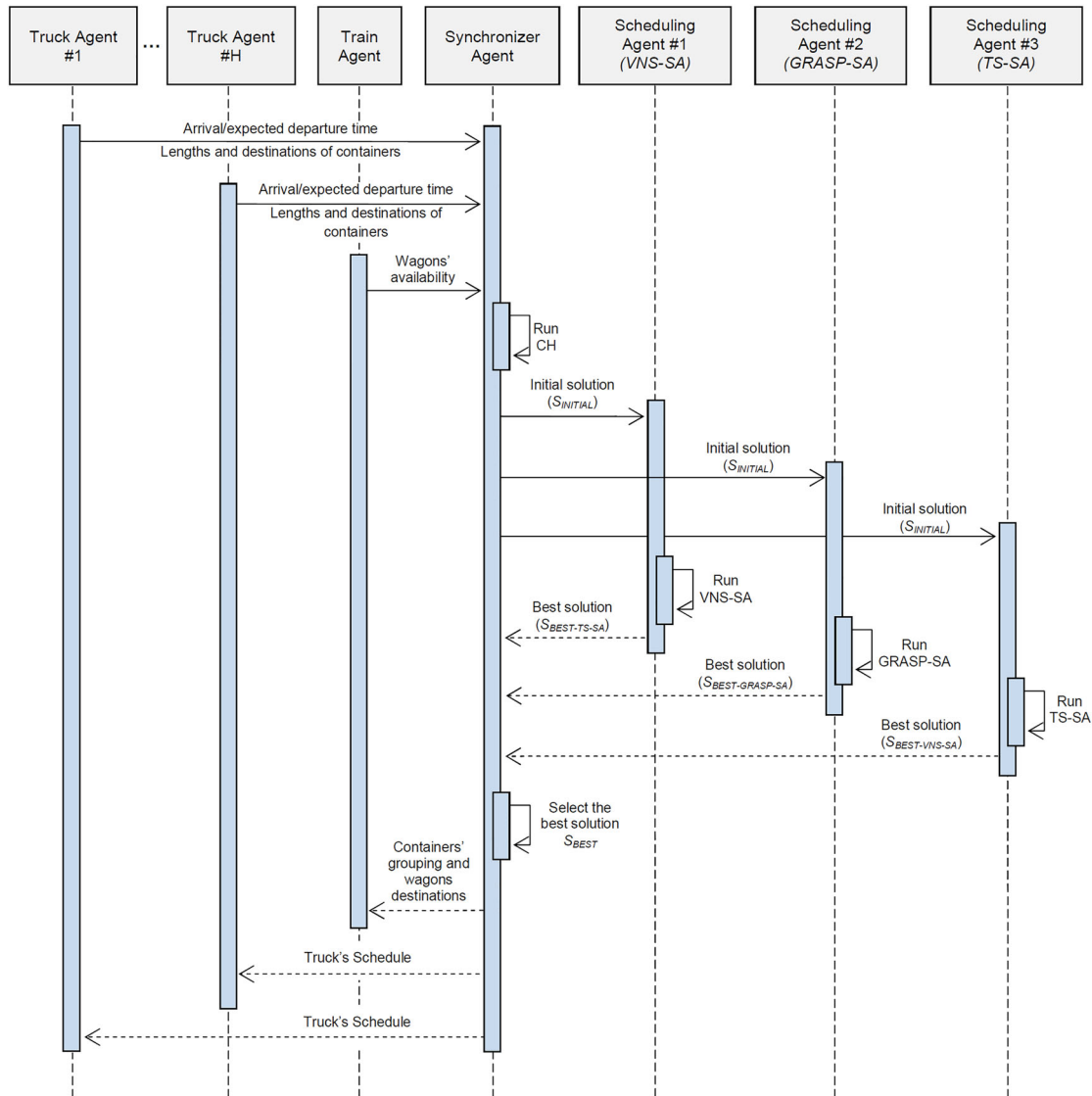


Figure 6. Sequence diagram of the proposed MAS.

#### 4.2.4. Scheduling Agents

There are three Scheduling Agents in the architecture of the proposed MAS. Each of them runs a different hybrid meta-heuristic: Variable Neighbourhood Search (VNS) (Mladenovic and Hansen 1997), Greedy Randomised Adaptive Search Procedure (GRASP) (Feo and Resende 1995) and Tabu Search (TS) (Glover 1989). Each of those three meta-heuristics is hybridised with Simulated Annealing (SA) (Kirkpatrick, Gelatt, and Vecchi 1983) which results in three hybrid meta-heuristics (VNS-SA, GRASP-SA and TS-SA).

SA is combined with three different meta-heuristics (VNS, GRASP and TS) in order to make use of the features of each algorithm and to provide a balance between the exploration (diversification) and exploitation (intensification) since SA has a fast convergence in a local optima. The VNS is chosen for its ability of dynamically change the neighbourhood of search to avoid local optima. The GRASP is selected for its multi-start feature coupled with local search. GRASP helps to escape from local optima. The TS is chosen for its ability to learn from the past by making use of memory during the exploring of the neighbourhood solutions. Indeed, the performed moves are stored in a tabu-list which gives the algorithm the ability to avoid the revisit of the solutions already encountered. Finally, for SA, when the temperature parameter  $Tmpr$  is high, the SA tends to accepts deteriorating moves. Then, as the temperature  $Tmpr$  decreases, the algorithm becomes very selective on the new generated solutions. Through testing and experiments we observe that each one of the three meta-heuristics has strengths and weaknesses depending on the configuration of instances and this is the main reason to run them in parallel.

---

**Algorithm 1:** Construction Heuristic of the Synchroniser Agent to build the Initial Solution

---

```
1: Receive PI-containers' destinations and lengths from Truck Agents and wagons'
   availability from the Train Agent
2: Sort all PI-containers in decreasing lengths by truck arrival
   time and group them by destination
3: Set: L[i] length of PI-container (i)
4: Set: AvL[w] available length in each wagon (w)
   (Initially AvL[w] = Q: Wagon's capacity)
5: Set: AvPos[h] average position of a truck (h)
6: Set: SumDist = 0 (A temporary variable to calculate AvPos[h])
7: For each destination d do
8:   For each PI-container (i) with destination (d) do
9:     For each wagon (w) do
10:      If wagon (w) is empty then
11:        Assign destination (d) to wagon (w)
12:      End If
13:      If L[i] <= AvL[w] and (i) and (w) have same destination then
14:        Assign the PI-container (i) to the wagon (w)
15:        AvL[w] = AvL[w] - L[i]
16:        Break (Select the next PI-container)
17:      End If
18:    End For
19:  End For
20: End For
21: For each truck (h) do
22:   SumDist = 0
23:   For each PI-container (i) do
24:     If PI-container (i) is in truck (h) then
25:       SumDist = SumDist + Position of the wagon that contains (i)
26:     End If
27:   End For
28:   AvPos[h] = SumDist / Number of PI-containers in truck (h)
29:   Assign truck (h) to the closest dock to AvPos[h]
30:   Set the start/end time for unloading truck h
31: End For
32: Calculate Objective Function
```

---

In the three Scheduling Agents, VNS, GRASP and TS are used for the sequencing of wagons' destinations and the grouping of the PI-containers, then, due to its fast convergence, SA (Algorithm 2) is used to find the best scheduling of the trucks at the docks for each combination of sequencing of wagons' destinations. All those three Scheduling Agents are concurrent and they run in parallel to improve the initial solution broadcasted by the Synchroniser Agent. In the three algorithms, three local search moves are considered: Insert, Swap and Insert + Swap. The insertion move consists of selecting a random truck and then inserting it in a different dock. The swap consists in the exchanging of the docks of two random different trucks. Finally, in the Insert + Swap move, a random truck is selected, inserted in a different dock and then swapped with another different truck.

**4.2.4.1. Scheduling Agent #1 (VNS-SA)** The first Scheduling Agent runs a hybrid VNS-SA. As presented in Algorithm 3, the Scheduling Agent #1 starts by loading the initial solution sent by the Synchroniser Agent. Then, a set of  $NbN$  neighbourhood structures is generated for the wagons' destinations sequencing. For each neighbourhood structure and at each iteration, the algorithm performs a local search move (Insert, Swap and Insert + Swap) with a probability of 1/3 for each move, then, it runs the Simulated Annealing (*See Algorithm 2*) to improve the trucks' assignments to the docks.

**4.2.4.2. Scheduling Agent #2 (GRASP-SA)** For the second Scheduling Agent, the GRASP is used for sequencing of wagons' destinations. As presented in Algorithm 4, the GRASP-SA Scheduling Agent starts by loading the initial solution broadcasted by the Synchroniser Agent. Then, for each global iteration, one of the three local search moves is performed, followed by the *SA\_Algorithm()* for the truck's scheduling. However, if the maximum local iterations *LocalMaxIt* is reached, then, a new sequence of wagon's destinations is generated.

---

**Algorithm 2:** Pseudo code of the Simulated Annealing *SA\_Algorithm()* for trucks' scheduling

---

```
1:   Input: Tmpr, S, SBEST, SNEW (SNEW is the new solution that contains the  
2:   While Tmpr > Epsilon do  
3:     Local Search move on trucks' scheduling at docks:  
       Insert, Swap or Insert +  
       Swap (Probability of each move = 1/3)  
4:     r = Random float (0 <= r <= 1)  
5:     If r < Exp((S - SNEW)/Tmpr) then  
6:       S = SNEW  
7:       If SBEST > SNEW then  
8:         SBEST = SNEW  
9:       Else  
10:        Cancel the Local Search move  
11:        Reduce Tmpr  
12:       End If  
13:     Else  
14:       Reduce Tmpr  
15:     End If  
16:   End While  
17:   Reset Tmpr to its initial value  
18:   Output: S, SBEST
```

---

---

**Algorithm 3:** Pseudo code of the hybrid VNS-SA

---

```
1:   Load initial solution SINITIAL received from Synchronizer Agent  
2:   Set: MaxGlobalIt, Tmpr, NbN, MaxShuffleIt  
3:   Set: SBEST = S = SINITIAL, MaxVNSIt = MaxGlobalIt / NbN  
4:   Generate a set NbN neighbourhood structures  
5:   GlobalIteration = 0  
6:   For each neighbourhood structure do  
7:     While GlobalIteration < MaxVNSIt do  
8:       Local Search move on wagons' destinations sequence:  
       Insert, Swap or Insert + Swap (Probability of each move = 1/3)  
9:       Run SA_Algorithm() to improve for trucks' scheduling (See Algorithm 2)  
10:      Shuffle PI-containers' sequencing after each MaxShuffleIt iterations  
11:      GlobalIteration ++  
12:     End While  
13:   End For  
14:   Return SBEST
```

---

4.2.4.3. *Scheduling Agent #3 (TS-SA)* In the third and last Scheduling Agent, the sequencing of wagons' destinations is managed using Tabu Search meta-heuristic. As presented in Algorithm 5, at each iteration, one of the three local search moves is performed. If the move is in the tabu list it will be cancelled, otherwise, it will be added to the tabu list. Then, the *SA\_Algorithm()* is called to improve the trucks' scheduling.

4.2.4.4. *Objective function* As mentioned previously, the objective consists of minimising:

- The number of used wagons
- The total distance travelled by the PI-containers from the docks to the wagons
- The trucks' tardiness

After performing each local search move (insert, swap or insert + swap) on the PI-containers and the trucks in the three Scheduling Agents, the objective function is calculated as follows: The first objective, which is the number of used wagons, is calculated using the assignment of the PI-containers to the wagons. Then, the total distance travelled by the PI-containers is calculated using their trucks' position at the docks and the average position of the wagon on which the PI-container is assigned to. The last objective is presented as the gap between the end time of the unloading and the expected departure time of the trucks.

---

**Algorithm 4:** Pseudo code of the hybrid GRASP-SA

---

```
1:   Load initial solution  $S_{INITIAL}$  received from Synchronizer Agent
2:   Set:  $MaxGlobalIt$ ,  $MaxLocalIt$ ,  $Tmpr$ ,  $MaxShuffleIt$ 
3:   Set:  $S_{BEST} = S = S_{INITIAL}$ 
4:    $GlobalIteration = 0$ ,  $LocalIteration = 0$ 
5:   While  $GlobalIteration < MaxGlobalIt$  do
6:     If  $LocalIteration == LocalMaxIt$  then
7:       Generate a new random sequence of wagons' destinations
8:        $LocalIteration = 0$ 
9:     End If
10:    Local Search move on wagons' destinations sequence:
11:    Insert, Swap or Insert + Swap (Probability of each move = 1/3)
12:    Run SA_Algorithm() to improve for trucks' scheduling (See Algorithm 2)
13:    Shuffle PI-containers' sequencing after each  $ShuffleMaxIt$  iterations
14:     $LocalIteration ++$ 
15:     $GlobalIteration ++$ 
16:  End While
17:  Return  $S_{BEST}$ 
```

---

---

**Algorithm 5:** Pseudo code of the hybrid TS-SA

---

```
1:   Load initial solution  $S_{INITIAL}$  received from Synchronizer Agent
2:   Set:  $MaxGlobalIt$ ,  $TL$ ,  $Tmpr$ ,  $MaxShuffleIt$ 
3:   Set:  $S_{BEST} = S = S_{INITIAL}$ 
4:   Initialize Tabu List:  $TL = \emptyset$ 
5:    $GlobalIteration = 0$ 
6:   While  $GlobalIteration < MaxGlobalIt$  do
7:     Local Search move on wagons' destinations sequence:
8:     Insert, Swap or Insert + Swap (Probability of each move = 1/3)
9:     If the Local Search move is in  $TL$  then
10:      Cancel the Local Search move
11:    Else
12:      Update the Tabu List  $TL$ 
13:    End If
14:    Run SA_Algorithm() to improve for trucks' scheduling (See Algorithm 2)
15:    Shuffle PI-containers' sequencing after each  $ShuffleMaxIt$  iterations
16:     $GlobalIteration ++$ 
17:  End While
18:  Return  $S_{BEST}$ 
```

---

## 5. Numerical results

### 5.1. Implementation and instances

To validate the proposed MAS and MILP, the three hybrid meta-heuristics (VNS-SA, GRASP-SA and TS-SA) are developed in Java. The agents are created and implemented in JADE platform (Java Agent DEvelopment framework) and all the experiments are performed in a PC with a 2.40 GHz Intel<sup>(R)</sup> Core<sup>(TM)</sup> i3 CPU and a 4GB RAM. The MILP model is implemented in IBM ILOG CPLEX Solver (Version 12.8). To evaluate the stability of the MAS, the tests are performed in 5 replications for each of the 34 instances, and the average value of the objective function is presented. A time limit of 3600s is set for CPLEX. The value of the weighting factor  $\alpha$ ,  $\beta$  and  $\gamma$  can be set by the user. In this study, those weighting factors are set to  $\alpha = 0.995$ ,  $\beta = 0.003$  and  $\gamma = 0.002$  to ensure the use of a minimum number of wagons while minimising the total distances travelled by the PI-containers as well as the trucks' tardiness.

In order to evaluate the two proposed models, several instances are generated randomly by changing the number of PI-containers  $N$  and their lengths  $L_i$ , the number of destinations  $D$  and the number of trucks  $H$ . The variation of those parameters is presented in Table 3.

For the MAS Scheduling Agents' parameters, the global number of iterations  $MaxGlobalIt$  is set to 250 for instances 1 to 20, and 1000 for the remaining instances. The SA initial temperature  $Tmpr$  is set to 1 and it is decreased by  $10^{-3}$  for instances 1 to 20 and by  $7.5 \cdot 10^{-4}$  for the other set of instances. For the VNS-SA Scheduling Agent, the number of neighbourhood structures goes from 1 to 3 depending on the size of instances.  $ShuffleMaxIt$  is set to 10. Finally, the local

number of iterations *MaxLocalIt* in GRASP-SA Scheduling Agent is set to 50 for instances 1 to 20 and 150 for the remaining instances.

In order to guarantee a good performance, the setting of the values of the parameters in the algorithms is a crucial issue. Those values are set for this case study after a tuning of parameters (not described in this paper). They ensure the best

Table 3. The variation of parameters in the generated instances.

Parameters	Values
Wagons ( <i>W</i> )	The train is composed of 30 empty wagons in all instances.
PI-containers ( <i>N</i> )	20 instances with 10 PI-containers and 14 instances with 15 PI-containers.
PI-containers' lengths ( $L_i$ ) in meters (m)	The lengths are selected among the values {1.2, 2.4, 3.6, 4.8, 6, 12}.
Destinations ( <i>D</i> )	The number of destination is selected among the values {2, 3, 4, 5, 6}.
Trucks ( <i>H</i> )	The number of trucks is selected among the values {2, 3, 4, 5}
Useful length of the truck	13.5 m
Number of docks in the Road-Rail section	28
Useful length of a wagon ( <i>Q</i> )	18 m
Full length of a wagon	20 m

Table 4. Comparison between the MILP and MAS results.

Instances				MILP					MAS					MAS vs. MILP
#	N	D	H	Wag	Dist	Tard	Obj	Time (s)	Wag	Dist	Tard	Obj	Time (s)	
1	10	2	2	2	64.28	0.0	<b>2.183</b>	1.42	2	64.28	0.0	<b>2.183</b>	1.38	<b>0.00%</b>
2	10	3	2	3	127.14	0.0	<b>3.366</b>	4.05	3	127.14	0.0	<b>3.366</b>	1.41	<b>0.00%</b>
3	10	4	2	4	144.28	0.0	<b>4.413</b>	8.34	4	144.28	0.0	<b>4.413</b>	1.72	<b>0.00%</b>
4	10	5	2	5	180.71	0.0	<b>5.517</b>	25.67	5	180.71	0.0	<b>5.517</b>	1.33	<b>0.00%</b>
5	10	6	2	6	200.00	0.0	<b>6.570</b>	34.89	6	200.00	0.0	<b>6.570</b>	1.38	<b>0.00%</b>
6	10	2	3	2	83.57	0.0	<b>2.241</b>	1.16	2	83.57	0.0	<b>2.241</b>	1.48	<b>0.00%</b>
7	10	3	3	3	124.29	0.0	<b>3.358</b>	5.89	3	125.29	0.0	3.361	1.49	0.09%
8	10	4	3	4	142.86	0.0	<b>4.409</b>	43.33	4	144.00	0.0	4.412	1.39	0.08%
9	10	5	3	5	200.71	0.0	<b>5.577</b>	29.00	5	200.71	0.0	<b>5.577</b>	1.28	<b>0.00%</b>
10	10	6	3	6	141.43	0.0	<b>6.394</b>	48.03	6	142.29	0.0	6.397	1.42	0.04%
11	10	2	4	2	80.71	0.0	<b>2.232</b>	1.33	2	80.71	0.0	<b>2.232</b>	1.50	<b>0.00%</b>
12	10	3	4	3	120.00	0.0	<b>3.345</b>	23.97	3	120.00	0.0	<b>3.345</b>	1.41	<b>0.00%</b>
13	10	4	4	4	100.71	0.0	<b>4.282</b>	32.17	4	101.71	0.0	4.285	1.39	0.07%
14	10	5	4	5	160.00	0.0	<b>5.455</b>	536.34	5	160.00	0.0	<b>5.455</b>	1.47	<b>0.00%</b>
15	10	6	4	6	122.14	0.0	<b>6.336</b>	169.27	6	124.71	0.0	6.344	1.42	0.12%
16	10	2	5	3	103.57	0.0	<b>3.296</b>	48.16	3	105.43	0.0	3.301	1.38	0.17%
17	10	3	5	4	101.43	0.0	<b>4.284</b>	34.33	4	110.57	1.0	4.314	1.44	0.69%
18	10	4	5	4	120.71	0.0	<b>4.342</b>	42.33	4	125.00	0.0	4.355	1.35	0.30%
19	10	5	5	5	123.57	0.0	<b>5.346</b>	425.45	5	137.43	0.0	5.387	1.39	0.78%
20	10	6	5	6	102.86	0.0	<b>6.279</b>	199.94	6	114.14	0.0	6.312	3.43	0.54%
21	15	2	3	3	162.50	0.0	<b>3.473</b>	7.09	3	165.64	0.0	3.482	3.02	0.27%
22	15	3	3	4	221.79	0.0	<b>4.645</b>	123.25	4	223.21	0.0	4.650	3.18	0.09%
23	15	4	3	4	224.64	0.0	<b>4.654</b>	39.77	4	225.64	0.0	4.657	3.19	0.06%
24	15	5	3	5	302.50	0.0	<b>5.883</b>	324.38	5	302.50	0.0	<b>5.883</b>	3.15	<b>0.00%</b>
25	15	6	3	6	263.21	0.0	<b>6.760</b>	122.95	6	263.79	0.0	6.761	3.15	0.03%
26	15	2	4	4	141.79	0.0	<b>4.405</b>	295.63	4	170.93	0.0	4.493	3.25	1.98%
27	15	3	4	3	180.36	0.0	<b>3.526</b>	274.25	3	180.36	0.0	<b>3.526</b>	3.28	<b>0.00%</b>
28	15	4	4	4	205.36	0.0	<b>4.596</b>	163.48	4	210.50	0.0	4.611	3.37	0.34%
29	15	5	4	5	285.36	0.0	<b>5.831</b>	591.11	5	286.07	2.0	5.837	3.31	0.11%
30	15	6	4	6	246.07	0.0	<b>6.708</b>	946.58	6	250.64	1.0	6.724	3.27	0.23%
31	15	2	5	4	161.07	0.0	<b>4.463</b>	1751.31	4	213.64	0.0	4.621	3.28	3.53%
32	15	3	5	4	223.93	0.0	<b>4.652</b>	1636.95	4	237.21	1.0	4.694	3.39	0.90%
33	15	4	5	5	242.50	0.0	5.703*	3600.00	5	247.79	2.0	5.722	3.43	0.35%
34	15	5	5	**	**	**	**	**	5	258.36	0.0	5.750	3.52	-
<b>Average</b>					<b>163.82</b>	<b>0.00</b>		<b>351.27 s</b>		<b>168.79</b>	<b>0.21</b>		<b>2.20 s</b>	<b>0.33%</b>

\*Best solution found by CPLEX within 3600 s (not optimal).

\*\*CPLEX goes out of memory for those instances.



trade-off between the performance and the quality of the solutions. Those parameters were set after having performed tests on several small instances by setting a parameter and then evaluating its impact on the solution. For example, the iterations parameters were set after observing the convergence behaviour. Thus, once the objective function becomes stable, the value of the parameter is set.

### 5.2. Results of the MILP and MAS

The obtained results are presented in Table 4. The optimal values are presented in bold. The parameters of the instances ( $N$ : number of PI-containers,  $D$ : number of destinations and  $H$ : number of trucks) are presented in the first four columns. The MILP results on CPLEX solver are presented in columns 5 to 9 which show respectively the number of used wagons, the total distance covered by the PI-containers, the trucks' tardiness, the objective function and the computational time for the MILP.

As it can be seen in Table 4 and Figure 7, as the size of the instances increases the computational time in the MILP model is significantly increased. CPLEX is able to find the optimal solutions for 32 instances, except for instance 33 on which the time limit of 3600 s is exceeded. For the instance 34, CPLEX goes out of memory without giving any feasible solution. In Table 4, columns 10 to 14 show respectively the number of used wagons, the total distance covered by the PI-containers,

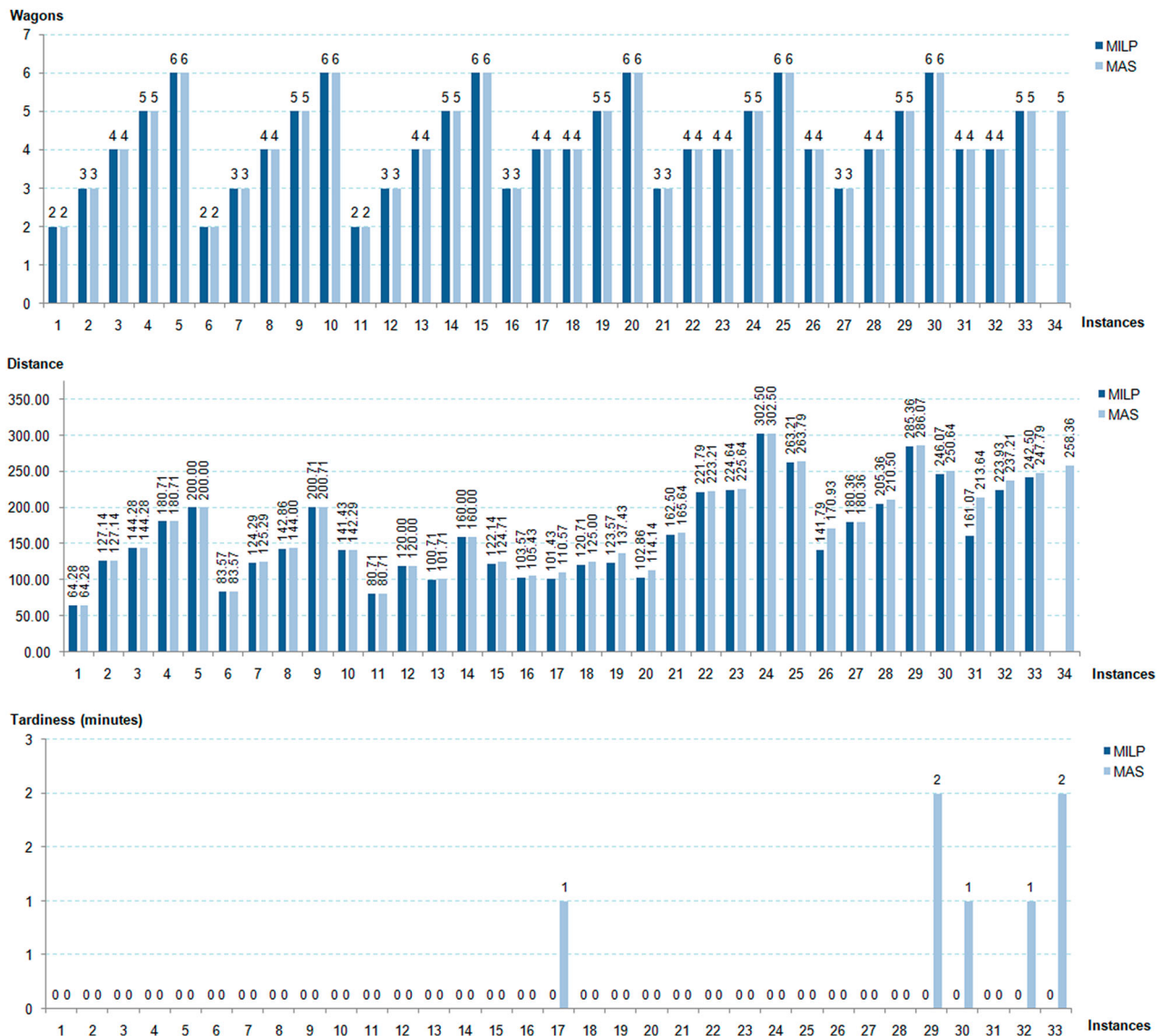


Figure 7. Objective function (wagons, distance and tardiness) in the MILP and MAS.

Table 5. MILP and MAS results for large instances.

#	Instances			MAS				
	N	D	H	Wag	Dist	Tard	Obj	Time (s)
35	30	8	8	8	539.29	1.00	9.580	4.51
36	30	15	12	15	512.43	0.00	16.462	5.13
37	40	10	20	11	830.28	0.00	13.436	7.13
38	50	15	25	17	1143.28	1.00	20.347	9.35

Table 6. Comparison between the schedule at the beginning of the day ( $S_{BEST}$ ) and the rescheduled solution at the end of the day ( $S_{RESCHEDULED}$ ) in the MAS.

#	Instances			$S_{BEST}$					$S_{RESCHEDULED}$					Dev (%)
	N	D	H	Wag	Dist	Tard	Obj	Time (s)	Wag	Dist	Tard	Obj	Time (s)	
1	10	2	2	2	64.28	0	2.183	1.38	2	94.00	0.00	2.272	0.82	4.08%
2	10	3	2	3	127.14	0	3.366	1.41	3	193.43	0.00	3.565	0.85	5.91%
3	10	4	2	4	144.28	0	4.413	1.72	4	207.14	0.00	4.601	0.81	4.27%
4	10	5	2	5	180.71	0	5.517	1.33	5	198.43	0.00	5.570	0.90	0.96%
5	10	6	2	6	200.00	0	6.570	1.38	6	208.57	0.00	6.596	0.86	0.39%
6	10	2	3	2	83.57	0	2.241	1.48	2	153.28	0.00	2.450	0.88	9.33%
7	10	3	3	3	125.29	0	3.361	1.49	3	211.86	0.00	3.621	0.92	7.73%
8	10	4	3	4	144.00	0	4.412	1.39	4	175.57	0.00	4.507	0.90	2.15%
9	10	5	3	5	200.71	0	5.577	1.28	5	222.57	0.00	5.643	0.93	1.18%
10	10	6	3	6	142.29	0	6.397	1.42	6	204.43	0.00	6.583	0.88	2.91%
11	10	2	4	2	80.71	0	2.232	1.50	2	217.14	0.00	2.641	1.08	18.34%
12	10	3	4	3	120.00	0	3.345	1.41	3	225.43	0.00	3.661	0.92	9.46%
13	10	4	4	4	101.71	0	4.285	1.39	4	232.71	0.00	4.678	1.15	9.17%
14	10	5	4	5	160.00	0	5.455	1.47	5	177.57	0.00	5.508	0.96	0.97%
15	10	6	4	6	124.71	0	6.344	1.42	6	181.57	0.00	6.515	1.07	2.69%
16	10	2	5	3	105.43	0	3.301	1.38	3	204.43	0.00	3.598	1.01	9.00%
17	10	3	5	4	110.57	1	4.314	1.44	4	200.71	13.00	4.608	1.24	6.83%
18	10	4	5	4	125.00	0	4.355	1.35	4	210.85	0.00	4.613	1.12	5.91%
19	10	5	5	5	137.43	0	5.387	1.39	5	199.71	1.00	5.576	0.91	3.51%
20	10	6	5	6	114.14	0	6.312	3.43	6	148.29	0.00	6.415	1.34	1.62%
21	15	2	3	3	165.64	0	3.482	3.02	3	316.92	0.00	3.936	2.68	13.03%
22	15	3	3	4	223.21	0	4.650	3.18	4	299.07	0.00	4.877	2.79	4.89%
23	15	4	3	4	225.64	0	4.657	3.19	4	405.35	0.00	5.196	2.71	11.58%
24	15	5	3	5	302.50	0	5.883	3.15	5	322.64	0.00	5.943	2.72	1.03%
25	15	6	3	6	263.79	0	6.761	3.15	6	308.64	0.00	6.896	2.95	1.99%
26	15	2	4	4	170.93	0	4.493	3.25	4	347.64	0.00	5.023	2.97	11.80%
27	15	3	4	3	180.36	0	3.526	3.28	3	358.07	0.00	4.059	3.11	15.12%
28	15	4	4	4	210.50	0	4.611	3.37	4	325.07	0.00	4.955	3.00	7.45%
29	15	5	4	5	286.07	2	5.837	3.31	5	337.36	0.00	5.987	3.59	2.57%
30	15	6	4	6	250.64	1	6.724	3.27	6	374.93	0.00	7.095	3.22	5.52%
31	15	2	5	4	213.64	0	4.621	3.28	4	351.35	0.00	5.034	3.49	8.94%
32	15	3	5	4	237.21	1	4.694	3.39	4	372.92	50.00	5.199	3.30	10.76%
33	15	4	5	5	247.79	2	5.722	3.43	5	356.93	1.00	6.048	3.78	5.69%
34	15	5	5	5	258.36	0.0	5.750	3.52	5	348.64	37.00	6.095	3.56	6.00%
<b>Average</b>					<b>171.42</b>	<b>0.0</b>	<b>4.729</b>	<b>2.24</b>		<b>255.68</b>	<b>3.00</b>	<b>4.987</b>	<b>1.87</b>	<b>6.26%</b>

the trucks' tardiness, the objective function and the computational time for the MAS. The last column shows the deviation between the objective function in the MILP and MAS. The deviation is calculated as follows (this formula is used also to calculate the deviation in Table 6):

$$\text{Dev.}(\%) = 100 * \left( \frac{\text{Objective}_{\text{MAS}} - \text{Objective}_{\text{MILP}}}{\text{Objective}_{\text{MILP}}} \right)$$

As it can be seen in the last column, the MAS is able to find the optimal solution (Wagons, distances and trucks' tardiness) for 12 instances within a short computational time (2.20 s) compared to CPLEX solver (351.27 s). The total average deviation of the objective function between the MILP and the MAS is 0.33% which validates the performance of the proposed MAS architecture also in term of the quality of the solutions. In order to push the meta-heuristics to their limits, several large instances are added. The obtained results are presented in Table 5.

As shown in Figure 8, when the number of destinations becomes higher, we can see a significant increase in the distances travelled by the PI-containers. Furthermore, we observe that while increasing the number of destinations, the number

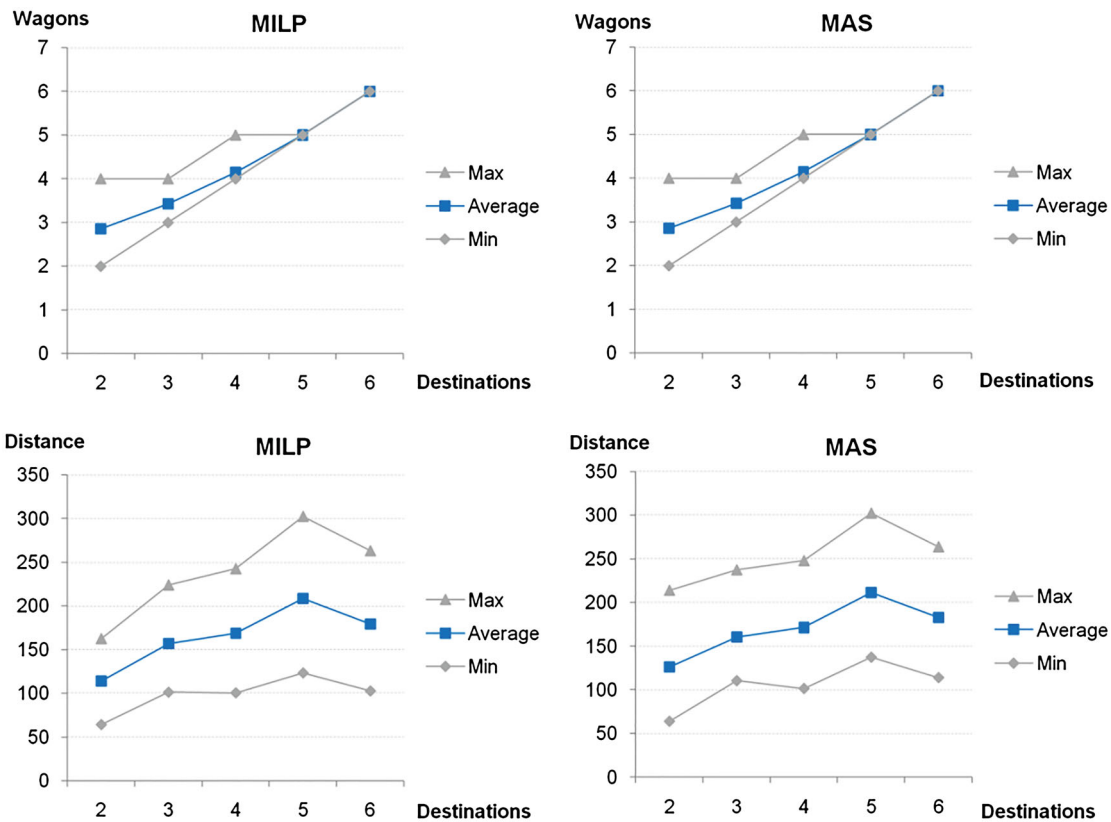


Figure 8. Impact of the number of destinations on used wagons and distances in MILP and MAS.

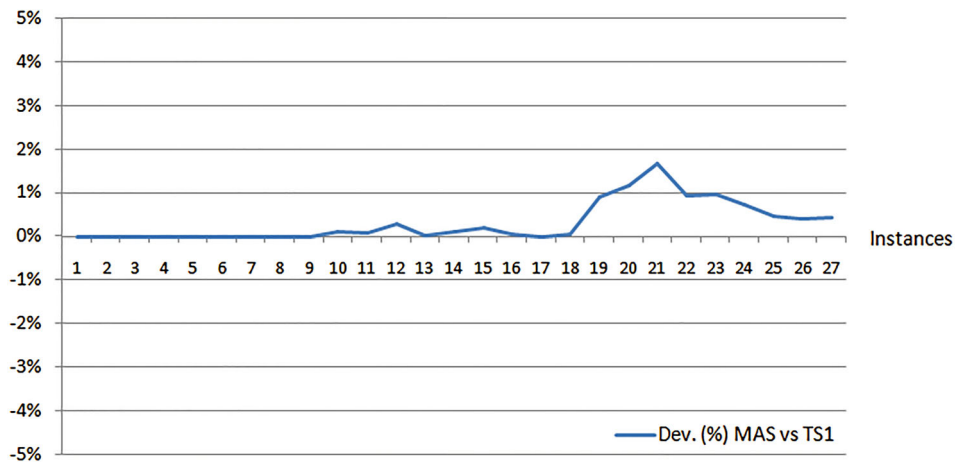


Figure 9. Deviation between the MAS meta-heuristics and the TS1.

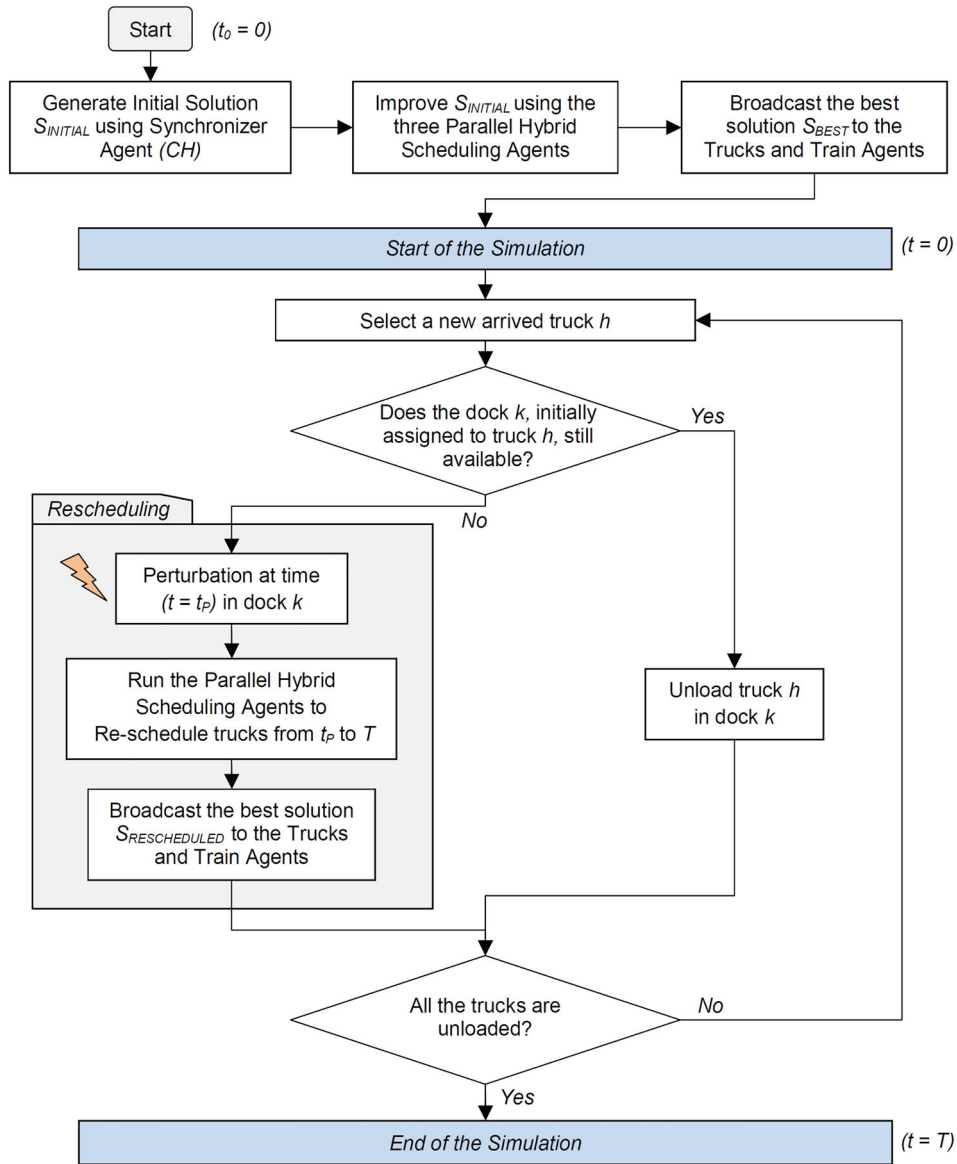


Figure 10. The rescheduling process in the MAS under perturbation.

of used wagons is also increased. For example, in instances 1 to 5, while keeping the same number of PI-containers, as the number of destinations goes from 2 to 6 the distance is increased from 64.28 to 200.00 and the number of used wagons becomes bigger. These results can be explained by the fact that when PI-containers have various different destinations, then, more wagons are going to be used since PI-containers with the same destination cannot be loaded in the same wagon on the one hand, and the PI-containers have to travel additional distances to reach their wagons on the other hand.

In order to evaluate the performance of the three meta-heuristics, a comparison test is done on benchmark instances from the literature. Since we could not find benchmark instances that perfectly match our problem, we slightly adapted the three meta-heuristics to solve the first set of benchmark instances ( $27 * 10 = 270$  instances) for the multiple door cross-docking problem presented in (Van Belle et al. 2013). As it can be seen in Figure 9, the three meta-heuristics provided solutions with small deviations from the results of the Tabu Search (TS1) in Van Belle et al. (2013). Appendix 1, presents the deviation between the meta-heuristics in the MAS and the Tabu Search proposed by Van Belle et al. (2013).

## 6. Assessment of the MAS robustness

In this section, the robustness of the MAS is evaluated under perturbations. In a real PI context, different perturbations may occur during the day. Those perturbations can be separated into internal perturbations such as docks' or wagons' unavailability or a conveyor that is not available for a specific period of time and external perturbations which are related especially to trucks' and trains' delays. In this paper, we consider the docks' failure, which is an internal perturbation to evaluate the reactivity of the MAS.

As illustrated in the flowchart of Figure 10, a schedule ( $S_{BEST}$ ) is generated at the beginning of the day using the three parallel hybrid Scheduling Agents presented previously. This schedule is then broadcasted to the Train and the Trucks Agents through the Synchroniser Agent. The simulation starts at time zero ( $t_0 = 0$ ) and each truck goes to the dock initially assigned to it for unloading. Then two cases may occur: the dock is available for unloading or the dock is not available for a period of time.

In the first case, if the dock is still available, the truck will be unloaded in that dock. However, in the second case, the MAS runs the three Scheduling Agents to find a new schedule for the trucks starting from the instant of perturbation ( $t = t_p$ ). Then, the new schedule is broadcasted to the Trucks Agents and the Train Agent.

As shown in the illustrative example in Figure 11, the perturbation occurs at dock 17 on which the truck number 3 was initially assigned to. This dock will be unavailable for 2h of failure. At the end of the failure, the dock will be available to be scheduled for other inbound trucks (for example truck 5 in Figure 11). In order to avoid additional tardiness for the truck number 3, a rescheduling is performed by using the three Scheduling Agents after being notified by the Synchroniser Agent for the temporary unavailability of dock 17. Once the new schedule is available, it is broadcasted by the Synchroniser Agent to the remaining trucks.

The simulations are performed on a time horizon of 10 hours in 5 replications; the average value is presented for each objective. At each replication, a perturbation is generated at a random dock for a period of 1 to 3 hours. The detailed simulation results for the MAS in case of no perturbations are presented in Table 6 starting from column 5 to 9. For the scenario with perturbations, the results are shown in columns 10 to 14. The deviation of the objective function between the two solutions  $S_{BEST}$  and  $S_{RESCHEDULED}$  is presented in the last column.

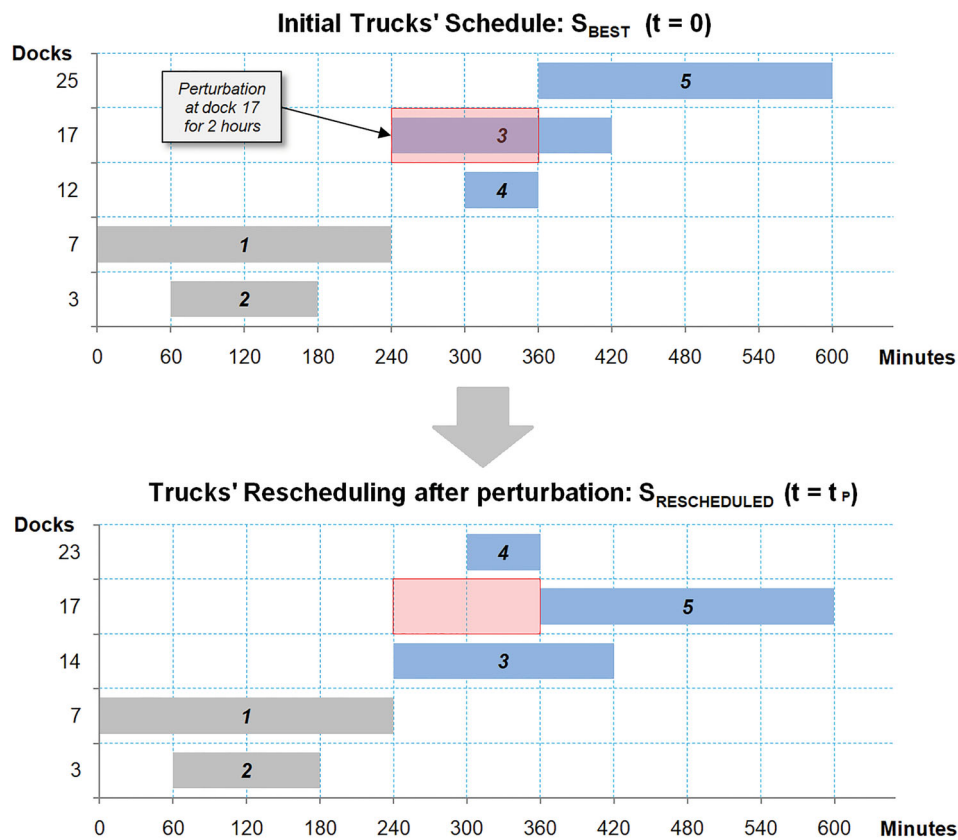


Figure 11. An illustrative example of trucks rescheduling after a perturbation of 2 hours at dock 17.

As it can be seen in Table 6 and Figure 12, the perturbations have no impact on the number of used wagons which remained the same for all the instances. However, the average distance increased significantly from 171.42 to 255.68. The trucks' tardiness remained also stable with few exceptions (instances 17 and 32). The average values in the last line of

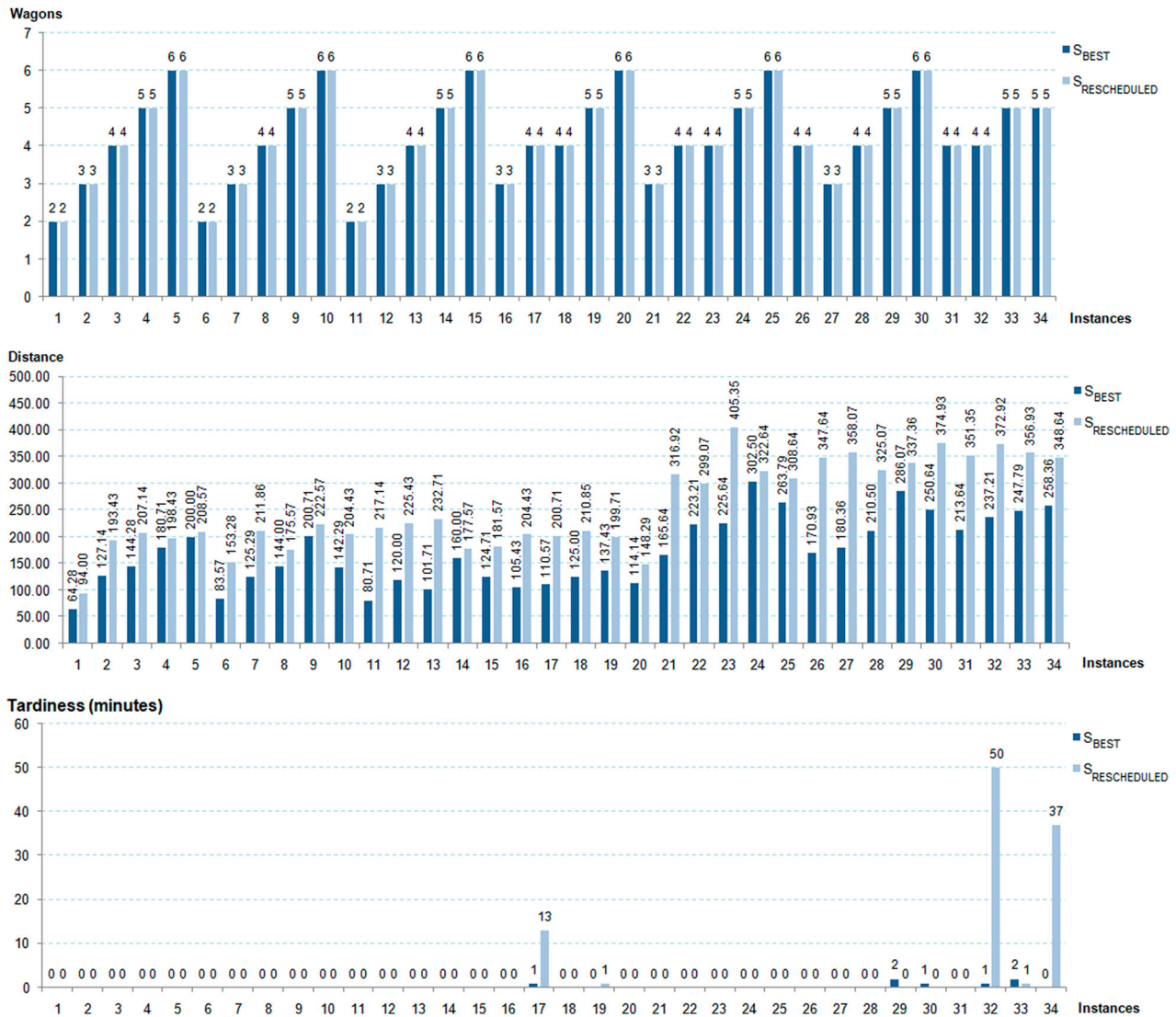


Figure 12. Objective function (wagons, distance and tardiness) in the MAS with and without perturbation.

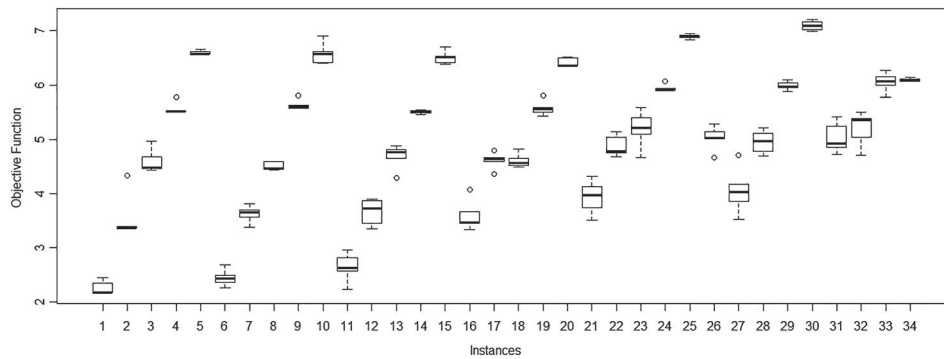


Figure 13. Boxplot of the MAS rescheduled solutions.

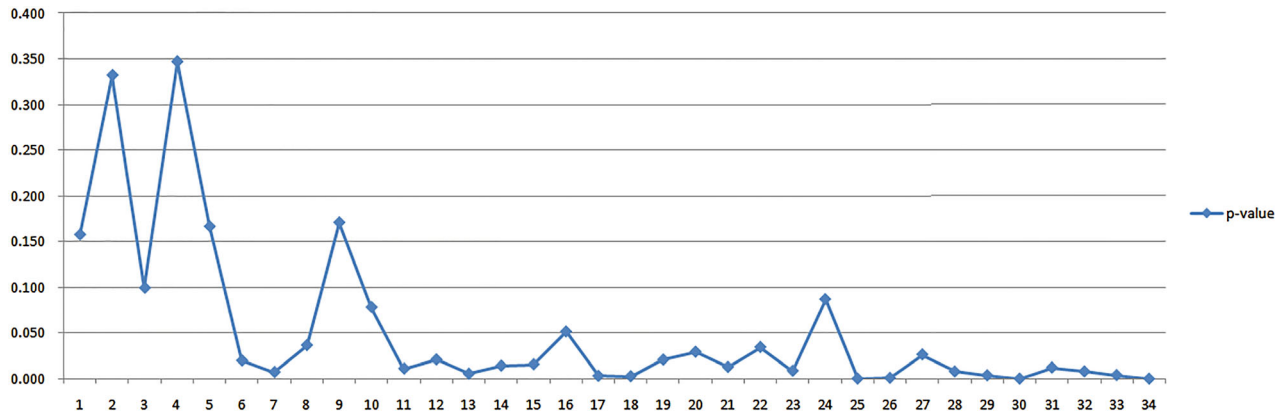


Figure 14.  $p$ -values for each instance in the ANOVA analysis.

Table 6 are calculated for all the instances 1 to 34. The total average deviation of the objective function is 6.26%. The computational time in column 14 of Table 6 is the time spent by the parallel Scheduling Agents to find the new reschedule for the remaining trucks after the perturbation.

Figure 13 presents a boxplot of the objective functions for the rescheduled solutions for 5 replications for each instance. In order to evaluate the impact of the perturbations on the quality of the solution (objective function) provided by the MAS, we run a one way ANOVA (Analysis of variance) for each of the 34 instances after checking the normality for the 5 replications of each instance using Kolmogorov-Smirnov test. The obtained ANOVA  $p$ -values for each instance are presented in Figure 14. As it can be seen, the perturbations have a significant impact on the initial solution since the  $p$ -value  $< 0.05$  for most of the instances (except for 9 instances). After additional testing, it seems that the quality of solutions start to be negatively affected when the unavailability the docks increases significantly.

## 7. Conclusion

In this paper, a multi-agent based model was proposed for the truck scheduling and PI-containers' assignment and grouping problem in a Road-Rail Physical Internet Hub. In order to maintain quality assured solutions, the architecture of the proposed MAS runs three parallel concurrent Scheduling Agents using three different hybrid meta-heuristics (VNS-SA, GRASP-SA and TS-SA). To ensure sustainability, the objective of the model was designed to optimize a weighted sum of three objectives: minimizing the number of used wagons, the total distance travelled by the PI-containers from the docks to the wagons in addition to the total tardiness of the trucks. The performance of the proposed MAS in a static environment was then evaluated using a mixed integer linear programming (MILP) formulation of the problem. The results validate the performance of the MAS which was able to find the optimal solution for 12 instances (vs. 32 for CPLEX solver) within an average computational time of 2.20 s (vs. 351.27 s for CPLEX) and a total deviation of 0.33% for the objective function. Finally, the reactivity of the MAS was tested in front of internal perturbations. Results showed that the total average deviation was 6.27% from the initial schedule, which illustrates the ability of the MAS to react effectively in a perturbed environment. This was validated through an ANOVA analysis.

A review of the literature showed that the implementation of the PI concept in the global supply chain optimization has a positive impact on the logistics efficiency and on the three pillars of sustainability: economical, social and environmental aspects. Since the PI literature focuses more on the global supply chain rather than optimizing internal operations occurring in the PI-nodes especially PI-hubs, this paper tried to fill this gap in the literature by addressing the scheduling and grouping problem in the Road-Rail PI-hub and suggesting a multi-agent model that can handle possible disruptions. In the proposed MAS, even though the obtained results are promising, further work is needed to investigate other aspects such as the real time routing of PI-containers in the PI-sorters and developing methods to find the shortest path for the PI-containers. Also, in this paper, negotiation was not directly addressed but the MAS model can be easily extended to integrate negotiation directly among trucks and docks in order to construct the alternative schedule. Therefore, since in the proposed MAS the decisions pass through the synchroniser, there is no direct negotiation between the trucks and other trucks or between the trucks and the docks. It will be interesting to integrate this characteristic in future models.

One interesting direction of this work is the conjunction of the PI concept with the Block Chain technology which has shown a positive impact on the sustainability of the logistics companies and global supply chain network Treiblmaier (2019). Additional constraints could also be considered, especially those related to the routing of the PI-containers in the PI-sorters.

Furthermore, the temporary storage zones will be also taken into consideration to handle PI-containers especially in case of possible trains' delays or non-availability of wagons. Since the proposed MAS considers the truck scheduling and PI-containers' grouping and rescheduling only in case of internal perturbations, it will be interesting to take into account other kinds of external perturbations such as trucks' and trains' delays or unexpected arriving trucks that need to be unloaded.

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No potential conflict of interest was reported by the authors.

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**Appendix 1. Results of the three meta-heuristics on benchmark instances**

Instances			TS1	Time (s)	MAS	Time (s)	Dev. (%)
L	L	L	518.300	0.164	518.300	2.599	0.000%
L	L	M	592.072	0.171	592.072	3.810	0.000%
L	L	H	837.478	0.155	837.478	2.633	0.000%
L	M	L	526.391	0.147	526.391	2.049	0.000%
L	M	M	654.059	0.153	654.059	2.648	0.000%
L	M	H	830.229	0.145	830.229	4.057	0.000%
L	H	L	684.285	0.167	684.285	5.353	0.000%
L	H	M	601.945	0.156	601.945	2.192	0.000%
L	H	H	957.740	0.152	957.740	8.816	0.000%
M	L	L	695.459	0.417	696.160	10.445	0.101%
M	L	M	962.622	0.425	963.485	11.406	0.090%
M	L	H	1236.073	0.407	1239.739	8.992	0.297%
M	M	L	615.812	0.437	615.941	11.576	0.021%
M	M	M	1004.442	0.411	1005.520	14.955	0.107%
M	M	H	1443.384	0.434	1446.299	11.138	0.202%
M	H	L	875.440	0.426	875.947	11.003	0.058%
M	H	M	1150.058	0.421	1150.058	11.916	0.000%
M	H	H	1704.644	0.506	1705.685	21.404	0.061%
H	L	L	1033.019	0.876	1042.466	24.987	0.915%
H	L	M	1197.026	0.846	1211.018	19.460	1.169%
H	L	H	1859.446	1.040	1890.713	22.067	1.682%
H	M	L	1037.082	1.010	1046.698	16.313	0.927%
H	M	M	1151.924	0.996	1162.979	23.357	0.960%
H	M	H	1985.397	1.011	1999.832	25.951	0.727%
H	H	L	1281.025	1.018	1286.852	26.828	0.455%
H	H	M	1712.346	1.139	1719.380	26.321	0.411%
H	H	H	2437.626	1.025	2447.986	25.595	0.425%
<b>Average</b>				<b>0.528</b>		<b>13.254</b>	<b>0.319%</b>