ADDRESSING THE IMPACT OF MAINTENANCE IN SHUNTING OPERATIONS THROUGH SHUNT-IN POLICIES FOR FREIGHT TRAINS OPERATIONS.

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ABSTRACT

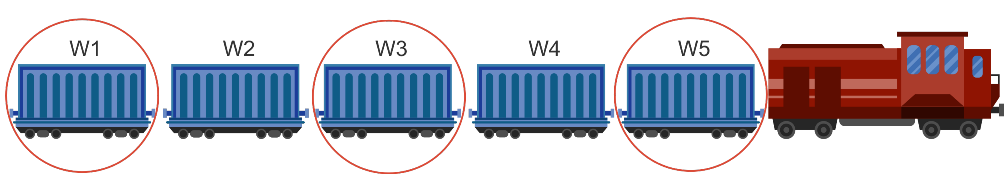
An efficient, reliable, and high-quality rail freight transport system in Europe is essential for the competitiveness of the European economy. In a context in which Europe aims to become climate-neutral by 2050, freight trains play a key role in this transition, given that almost 78% of freight is currently transported by road. For this reason, the optimization of shunting operations has already proven to be effective in terms of costs to be sustained by companies. Our study aims to assess the impact of the maintenance constraints on freight train management in the long term, with a specific focus on how shunting operations are affected by these maintenance constraints and other freight train management KPIs. To address this problem, we present different Shunt-In policies, which deal with how to assign wagons to an outbound-train. To assess the validity of the methodology, several simulations are performed, exploiting a projected timetable from 2020 to 2040 used by the Luxembourg National Railway Company with a particular focus on the Bettembourg Eurohub Sud Terminal connecting several EU countries. The results are compared to both a No-Maintenance scenario and data provided by practitioners. We demonstrate that mileage-based maintenance impacts on different aspects of freight management. Moreover, the choice of which wagon to place in an outbound train can be crucial in optimizing the operation, affecting up to 20% of the overall number of shunting operations. Finally, we prove that each policy provides better results compared to the Benchmark.

Keywords: Shunting Operations, Freight Train Operations Management, Fleet Optimization, Mileage-based Maintenance

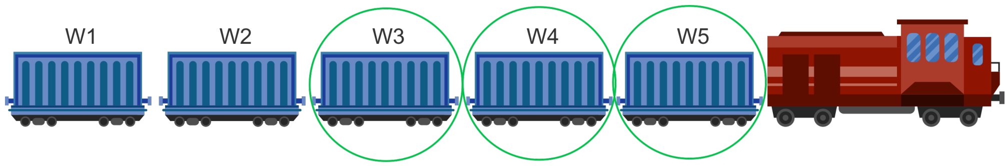
INTRODUCTION

Global trends in transport development show an ecological priority combined with energy efficiency. Data from the European Environment Agency (EEA) (*1*) show how transport produces the largest greenhouse gas emissions in Europe and is, therefore, the main cause of air pollution in cities, accounting for 27% of total EU emissions, where 95% of them come from cars, vans, trucks, and buses (i.e., road transport). In the context of the green transition, freight rail transportation play a key role in decongesting roads, which is one of the current priorities in transport policy (*2*), since almost 78% of freight is transported by road transport. Therefore, the freight train traffic is expected to double in the next 30 years to help achieve the goal of carbon neutrality (*3*). Nevertheless, freight transportation has costs that are inherent to the mode, as well as logistical complexities that do not exist for road transport. Some of these costs are related to the operations performed within shunting yards, namely, *shunting operations*.

The shunting yard is an area at specific stations consisting of parallel tracks where trains are disassembled and reassembled, loaded and unloaded according to their destinations. Cadarso et al. (*4*) define the shunting operation as the movement of one or multiple rolling stocks within a shunting yard. These operations can be performed mainly for two reasons: (a) demand adaptation, which we define as when an inbound train has to change its composition for its next service, and (b) maintenance, which is performed when it is necessary to remove one or several wagons from the train for maintenance reasons, which typically occurs when a wagon's mileage exceeds a specific threshold and therefore requires an inspection or visit a workshop for repair. From now on, we will refer equally to these kinds of shunts as mandatory shunts. According to practitioners, a shunting operation can last up to 15 minutes and can cause up to 20% of train delays and cancellations for freight transport companies, costing around 350 € per operation. It becomes clear how mismanagement of shunting operations for freight trains can have a huge impact in terms of train delays and cancellations, and operational costs. Despite the complexity of the problem, these movements are usually handled by practitioners in a suboptimal way, usually considering only the time required to fulfill the demand of an outbound train. Covering the demand of a train with random wagons without other parameters, e.g. the mileage performed so far, which in turn is linked to contractual clauses and maintenance thresholds, leads to an additional number of shunting operations to be performed in the long term. This occurs because one wagon or n wagons can be moved altogether for the same time and cost (*4*). This is shown in Figures 1a and 1b, where the impact of having adjacent and non-adjacent shunting operations are presented, while in Figure 1a are required three shunting operations to satisfy the demand of the outbound train, in Figure 1b only one operation is required.



(a)



(b)

FIGURE 1: Shunting operation of non-adjacent (a) and adjacent (b) wagons.

The clustering presented in Figure 1b allows the optimisation of the shunting operations. In addition, since each train is usually assigned to one service, a suboptimal choice of wagons to place can create systematic problems of recurring useless shunting operations. In this case, a solution could be to reduce the number of shunting operations performed for maintenance reasons. These types of shunts are likely to occur more than once per year, since, on average, operating wagons visit a workshop several times a year, and quite often these visits are unplanned (*5*). In addition, wagon maintenance is not a trivial task for companies, since it requires significant time, resources, and the unavailability of the supply for a certain time. In practice, maintenance is usually not integrated into the train composition process, but is instead solved as another separate problem that needs to be addressed, usually without considering how this may affect long-term operations. Since freight rail transport has one of the lowest priorities in the railway network (*6*), the efficient performance of shunting operations is one of the main objectives to reduce late departures of outbound trains. In fact, a late freight train departure can reduce its reserved time, which is given by the sum of two terms: (a) the recovery time (i.e., the additional time included in train timetables above the minimum necessary travel time) (*7*), and (b) the buffer time (i.e., the time to absorb the deviation from the scheduled path and prevent delay propagation between consecutive trains) (*8*). Larger time reserves allow to increase train punctuality, but, on the other hand, they reduce the capacity usage of the lines (*9*). In a context in which we expect to double freight traffic by 2050, the optimization of shunting operations becomes relevant given that time reserves are destined to be reduced. This is a hot topic for Europe, as the capacity of its rail network is already at a level that is increasingly challenging to guarantee an acceptable level of service, due to the increased frequency of all trains given the increased demand (*10*). Besides, due to contract fees and lack of deliveries of high-value freight, mismanagement of shunting operations can trigger a cascading effect of train delays and cancellations. The chosen approach for understanding the impact of this maintenance constraint on the shunting operation and from a strategic point of view is to develop a simulation environment. This helped quantifying the impact of these long-term limitations. To address this problem, we developed what we define as Shunt-In policies, which are different criteria for choosing which wagon to place on an outbound train to satisfy its demand. The rest of this paper is structured as follows. Section 2 summarizes the relevant studies found in the literature for this problem. Section 3 presents the problem description, the explanation of the tool used to assess the impact of the maintenance constraints, the policies, the different assumptions, and a description of the case study. Section 4 presents the results of the methodology applied for our case study, which is a 20 years simulation of Bettembourg shunting yard, a multimodal shunting yard in Luxembourg. Section 5 provides concluding remarks and future research directions.

LITERATURE REVIEW

This section presents the relevant literature review to this problem, focused on how operations are performed in the freight rail industry, where maintenance impacts, how it is generally performed, how shunting operations are usually performed and modeled in the literature, and the research gap we address with this research.

Shunting Operations

The shunting operation is defined as the movement of one or multiple wagons within the shunting yard. These movements can be done for multiple reasons and are modeled in the literature through the Rolling Stock Problem (RSP) and the Train Unit Shunting Problem (TUSP). The RSP is defined as the planning of a service time for each wagon and can be seen as the best way to manage the wagon and/or train units in order to reduce the cost of supplying the services or to satisfy the demand. Instead, the process of parking unused rolling stock units along with various related processes within a yard is called shunting, with the corresponding planning problem defined as the TUSP (*11, 12*). For Giacco et al. (*13*), the management of rolling stock is the major cost factor for each railway company, and the main cost factor is also the one with the greatest competitive impact, since the quality of the service depends on it. They solved the RSP problem with a two-step approach that combines scheduling tasks related to train services, short-term maintenance operations, and empty runs. Usually, for shunting operations on both passenger and freight trains, the RSP problem is solved first, followed by the TUSP. Given the clear independence of these two problems, an integrated approach has been proposed in another study: the Integrated Rolling Stock and Unit Shunting Problem (IRSUSP) (*14*). Similarly, Li et al. (*15*) presented a simulation approach with the implementation of different shunting policies with the aim of reducing operating costs for the entry and exit system of wagons considering a set of different strategies.

Shunting Yard Strategic and Tactical Tasks

In the shunting yard, also called the classification or marshalling yard, inbound trains are disassembled and then wagons are assembled such that desired compositions of outbound trains are generated, and these classification procedures are rather resources consuming. In fact, shunting operations may occupy between 10% and 50% of the total transit time of trains (*16*), while diesel-powered traction is still widely used in railway systems (*17*). These numbers prove that saving time and fuel in shunting operations can lead to significant reductions in delays and costs across the rail network. This is also the reason why many research studies have been done on how to use shunting yards efficiently. As indicated by Boysen et al. (*18*), hierarchical decision problems in a classification yard focus on two main types of tasks:

- *Strategic tasks*, which do not concern only the shunting yards, but are also related to investments and modifications of the infrastructure. A distinction is made between super-ordinate strategic decisions *in* shunting yards (e.g., should there be investments in high-cost equipment in a yard, for example, a new switch control?), and sub-ordinate strategic decisions which are taken at shunting yards (e.g. number of wagons and investments in medium-cost equipment);
- *Tactical tasks*, which must be resolved in a shorter planning horizon and generally affect organizational processes and shunting policies. Super-ordinate tasks have a direct effect on the network planning and sub-ordinate tasks only affect the organization of the yard, (e.g., planning wagon priority rules, sorting, and blocking) (*19–23*).

To the best of our knowledge, most papers on shunting yard operations deal with tactical tasks, such as the *Wagon Classification* Problem (WCP), where the focus is on the exact sequence of shunting steps in the classification area. Wagon maintenance scheduling, configured as a subordinate tactical task it shunting yards, plays a minor role in the literature. This may be due to the fact that this task is not specific to shunting yards. Nonetheless, it can be considered as a subproblem of the *Train Makeup* Problem (TMP), i.e., the assignment of wagons to outbound trains. In the real world, the train makeup problem may occur in a large number of factors depending on what particular constraints are added due to the shunting yard conformation and how the integration is elaborated in the hierarchical decision framework.

Wagon Maintenance

One of the most important cost factors in shunting operations is wagon maintenance (*24*). In fact, wagons spend a significant part of their downtimes associated with maintenance and repair in the workshop, producing overhead (i.e., a group of wagons is required) and variable costs (i.e., storage costs). Stazzone (*25*) explains how wagon maintenance follows a schedule driven by one of several triggers: mileage, time, or condition monitoring. While time-based methods were traditionally used, a large portion of operators now prefers to use mileage-based or condition-based maintenance since , on average, rolling stock is idle 70% of the time within the shunting yard without being used, leading to additional costs and inefficient maintenance operations.

Budai et al. (*26*) proposed a solution for the *Preventive Maintenance Scheduling* problem (PMSP) by modeling the problem with a modified scheduling problem and minimizing the overall cost with a greedy heuristic. Similarly, av et al. (*27*) solve both the *Rolling Stock problem* (RSP) and the maintenance scheduling for passenger trains, considering not only a preventive maintenance schedule but also a level of degradation based on the distance traveled by the rolling stock (i.e., the objective function aims to maximize the functional life of each train).

When organizing wagons maintenance, practitioners need to consider two macro-issues: which wagon in the in-bound train requires shunting due to maintenance regulations, and which shunting yard wagon should be replaced; how to implement a traffic schedule that guarantees traffic safety (*28*). Our study is framed within the first decision problem, since, for most of the literature, how many and what types of wagons should be replaced is an assumption (*29*). As already stated, maintenance constraints, seen as a threshold after which the wagon must pass through a maintenance check, affect shunting operations in multiple ways: by creating unavailability, which can lead to the choice of a sub-optimal wagon for the outbound train, generating the need to perform additional shunting operations to meet the demand of an outbound train, that would generate an additional time requirement to pick up a wagon from the shunting yard.

Research Gap

The problem of the studies mentioned above focuses more on the minimization of the overall operating cost, without considering how maintenance impacts the whole ecosystem of the freight railways, but rather they generally solve it as another problem of shunting operation. As highlighted before, rolling stock maintenance plays a key role in operations and is not done efficiently, leading to additional operations, lack of supply, and an increase in the overall cost. In addition, if a heterogeneous fleet is considered, more constraints must be considered to reduce the optimality of the solution.

METHODOLOGY

To assess the impact of maintenance on the shunting operation and the overall system from a strategic point of view, a simulation framework has been developed together with CFL Multimodal, the Luxembourg freight railway company. To address the problem of the impact of these constraints, we developed different Shunt-In policies which can be viewed as a greedy heuristic that chooses which rolling stock should be fitted within an outbound train based on different criteria.

Notation

- $W = D \cup O = \{1, 2, ..., m\}$ = Set of wagons w used by the rail system
- $w \in W$ = positive integer describing the unique code associated with each wagon in the rail system
- O = set of operating wagons w
- $D = A \cup U$ = set of all wagons w in the depot
- A = set of wagons w available in the depot D
- $U = R \cup M$ = set of wagons w unavailable in the depot, due to their assignment to a departing train or the reaching of the max mileage m_w
- R = set of wagons w unavailable in the depot due to their assignment to a departing train
- M = set of wagons w unavailable in the depot due to the reaching of the max mileage m_w
- T = set of wagons w on the oncoming train
- $r^T \in \mathbb{N}$ = distance of the trip that the departing train T has to perform
- $req_j = \begin{cases} 1, & \text{if the wagon type requested in } j\text{-th position in } T \text{ is of simple type} \\ 2, & \text{if the wagon type requested in } j\text{-th position in } T \text{ is of double type} \end{cases}$
- $S_{T_j} \subseteq A = \{w \in A | r^T \leq m_w - a_w \wedge t_w = req_j\}$ = set of suitable wagons with respect to wagon j to be shunted in the train T, based on the outbound train's demand
- $SH_T = \{y_w | w \in T\}$ = set of operations to be eventually performed on each wagon w on the oncoming train T, where $y_w \in \{0, 1, 2\}$. $y_w = 0$ means *Not to be shunted*, $y_w = 1$ means *Wagon to be shunted for maintenance* and $y_w = 2$ means *Wagon to be shunted for demand matching of the departing train T*
- $t_{loading}$ = time required for a single loading/unloading operation
- t_{sout} = time required for a shunt-out operation
- t_{sin} = time required for a shunt-in operation
- τ = timetable with services to be fulfilled

Assumptions

As described in the Literature Review, we consider for this analysis two types of situations in which one or multiple shunts are required: demand change and maintenance constraint.

Demand Shunts

First, when an inbound train must change composition, it must be chosen which wagon should be shunted to meet the demand. For each wagon, a type t_w, expressed as an integer that can take value 1 or 2, corresponding respectively to the type *SIMPLE* or *DOUBLE*. These two categories are related to the wagon models and are based on the wagon tare. In this study, a positional method is not used for the wagons since we consider two types of rolling stock and not models with different features and performance. Instead, we first calculate the difference in terms of t_w between the inbound train and the outbound train. Then, the wagons to shunt-out from the train are selected based on the calculated difference and the policy criteria. If one of the wagons chosen to be shunt-out from T has exceeded its maximum mileage m_w for demand reasons, then this wagon will be sent directly to maintenance. Then, an intermediate list of wagons is created with the new train composition.

Maintenance Constraint

Then for the second type of mandatory shunt (i.e.,the maintenance shunt), each wagon w is associated with an actual mileage a_w and a max mileage m_w before maintenance, expressed as integers. The maintenance constraint can be described as: $a_w \geq m_w$ where, if this condition is met, the wagon w must be removed from the inbound train to be sent to the workshop.

Choosing the mileage-based approach has been found to be a suitable solution for our simulation approach, as it is one of the most effective maintenance approaches for the rail industry at the moment (*25, 30*). At the end of this step, the final composition of the outbound train is obtained with the respective wagons to be placed.

Computing time to Shunt-In

In this research, for the time required for the shunting operations, we assume that:

- For the entire shunt-out operation to be performed, a time t_{sout} is required. Usually, this time is fixed.
- For the entire shunt-in operation to be performed, once the wagon has been chosen for a specific policy, we extract the necessary time t_{sin} from a normal distribution.

The choice of the t_{sin} has been done for multiple reasons: first, the policies do not take into account the time required for a wagon to be moved from the shunting yard into the outbound train, instead they try to look more at a more distant time horizon, trying, for example, to optimize for example the average mileage inside the train, or balancing the number of trips performed by each wagon. Second, and most importantly, this approach for the t_{sin} has been chosen in order not to reproduce *physically* the shunting yard, with the related TUSP problem, that could have led to too-tailored results. Instead, a more general approach assuming no optimization on the shunting movement has been chosen. To do this, we compute a normal distribution based on the average time μ and standard deviation σ^2, $\mathcal{N}(\mu, \sigma^2)$, let it be Δ. This distribution represents the time required to pick a random wagon from the shunting yard. Then, when a wagon w is chosen by a policy, we extract the time t_w required from Δ and, using it as the average time together with a fixed standard deviation, let it be ζ^2, we compute a second distribution $\mathcal{N}(t_w, \zeta^2)$, let it be $\Delta_{|SH_t|}$ for each position to be fulfilled in the train. Then, we extract t_{sin} from $\Delta_{|SH_t|}$. This second distribution represents the time required to move a random wagon into a random position inside the train, constrained to the number of wagons to be shunted in. This way, we're giving more reality to the problem, assuming that no optimization is being performed on the movement of the shunting yard without losing generality. Then, to explain the problem, we introduce additional notation, which will be explained in the Policies section.

Simulation

The simulation environment has been developed by the University of Luxembourg in collaboration with CFL Multimodal. This tool has been created in order to assess the impact of the maintenance constraint in the long term, since performing a tactical analysis could lead to sub-optimal decisions in a longer time horizon. Moreover, this tool is working together with the data provided by the company for the case study, This event-based simulation, developed in Python, reproduces the behavior of a shunting yard, and it requires as input the following information:

- a timetable with all the services τ, and data on the load of each train for both inbound and outbound trains;
- a list of wagons W;
- a list of time parameters, which are the usual time required for specific operations (for example additional time for checking when maintenance happens).

A flowchart of the operations performed inside the simulation for each train entry is here represented in Figure 2.

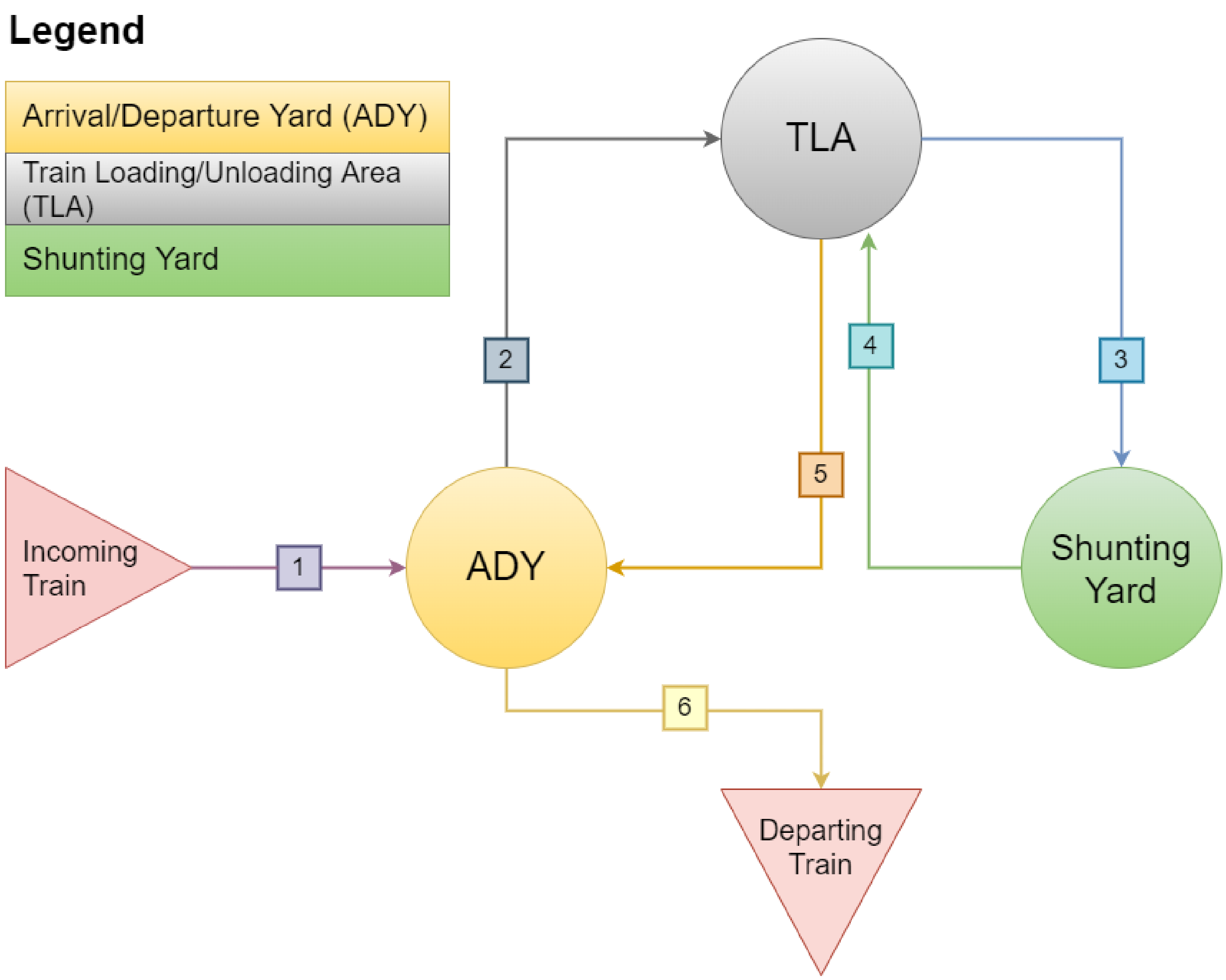


FIGURE 2: Flowchart of the operations performed in the simulator for each train

Given a train $T \in \tau$, as soon as it enters the system, it is moved into the queue of the Arrival/Departure yard (from now on referred as ADY) where it has to wait until the Train Unloading/Loading area (from now on referred as TLA) is free. Then, as soon as the TLA is free, T is moved there to perform the Unloading operation. Each loading/unloading operation, computed from the timetable in input, requires $t_{loading}$ time to be fulfilled. After the TLA, T is moved to the queue for Shunting Operations, either for demand matching or maintenance. For each shunt-out operation, a specific time t_{sout} is required, while for each shunt-in operation, a time t_{sin} is required.

After all shunting operations are performed on T, the train is then moved again to the queue for TLA for the loading operations. Again, after loading operations, the train is then moved again to the ADY ready for departure. At the departure time of T, or if the train has arrived at the ADY later than its scheduled departure time, the train departs. Otherwise, the train T is canceled. In both cases, the trip route r^T is applied to all the wagons of the train. In this paper, we will not consider any rescheduling throughout the simulation, but when cancellation is required we assume that the train is rescheduled before its next arrival at the station and without impacting in any way the operations.

Policies

In this section, the different Shunt-In policies developed are developed. Since we have two types of mandatory shunts, these policies apply any time a wagon must be chosen to be shunted. Four policies have been developed and explored: MIN, NCLD, AVG Long-Short, and Reserving.

MIN Policy

MIN policy aims to choose wagons from the shunting yard for the outbound train based on the $w^* = \text{argmin}_{w \in S_{T_j}} a_w$. The selected wagon will belong to the suitable set associated with the train T and the type of the wagon requested req_j in position j that have to be shunted, due to the composition of the departing train or maintenance need. The idea is to always provide to the departing train T the wagon with the minimum actual mileage a_w in order to decrease the average actual mileage on the train and allow it to be shunted as late as possible. For the removal due to demand, we'll pick the wagons in the train with the highest maximum mileage.

NCLD

This policy, which stands for *miNimum distanCe simiLar Deadline*, aims to choose wagons with a similar *index of use* to the average index of use of wagons not to be shunted out, in order to optimize the shunt-out operations that have to be performed when a maintenance occurs through the creation of clusters of similar mileage. For this policy three new elements will be introduced:

- α_w, index of use of a wagon on the train after the trip r^T;
- β_w, index of use of a wagon on the depot after the trip r^T;
- C, set of wagons on the train not to be shunted, with n cardinality of the set C.

Both α_w, index of use inside the train, and β_w, index of use between the suitable wagons are computed as $\frac{a_w + r^T}{m_j}$. However, while α_w is referred to as the wagon on the departing train, β_w is referred to as the ones in the suitable set S_{T_j} associated with the train T and the type of the wagon in position j. NCLD policy aims for homogeneity of the index of use for the wagons which are to be selected for the train T. The structure of this policy aims to maximize the usage of each wagon, trying to utilize as much as possible rolling stock that well fits the average mileage performed by wagons inside a train. Therefore, fewer wagons are needed to find a feasible solution, but more shunting efforts are required. For the removal due to demand, we'll pick the wagons in the train with the highest α_w.

AVG Long - Short

To describe this policy we will consider: δ_w, the *degree of unbalance* of a wagon in the depot and $tresh$, the threshold based upon which we consider r^T either a long or short trip. This heuristic aims to keep the balance of miles performed by each wagon by computing the degree of unbalance, which gives us a clue about the previous behavior of the wagon w, as $\delta_w = long_w - short_w$, where $long_w$ is the number of long-distance trips performed, while $short_w$ is the number of short trips performed. When a wagon has performed a considerable number of long trips, it is reasonable to think that it has used most of its max mileage and so it might perform only short trips. Therefore, it will be assigned to a short trip, in order to maximize the number of services that can be performed with the residual mileage. For the removal due to demand, we'll pick the wagons in the train based on the destination they are assigned to: if it is a short trip, we will choose the wagon w^* in T with the min δ_w, otherwise, if it is a long trip we will aim for the one with the max δ_w between the remaining ones.

Reserving
To describe the *Reserving* policy two elements need to be introduced: β_w, the degree of use of a wagon in the depot considering the trip r^T; $tresh$, the threshold for considering r^T either a long or short trip. This heuristic considers two possible scenarios: if the train T will perform a long trip, based on r^T, we prefer to use the wagon with the lowest mileage in the depot D and this information is given to us by β_w. Contrariwise, for a short trip, we want select from the depot, the most used wagon that can perform that trip r^T. In this way, it is allowed a good rotation of the fleet and, therefore, maximizes the trips that a wagon can perform before going to maintenance while satisfying the demand and having a homogeneous use. For the removal due to demand, a similar approach to AVG L-S is used. We'll pick the wagons in the train based on the destination they are assigned to: if it is a short trip, we will choose the wagon in T with the min β_w, otherwise if is a long trip we will aim for the one with the max β_w between the remaining ones.

Benchmark
For the Benchmark analysis, we developed a policy that randomly selects wagons from the shunting yard, as is now the case in the state of the art. To validate this approach, we saw that the values generated with a one-year simulation match the data provided by the practitioners in terms of rolling stock used, shunting operations performed, and annual mileage performed by the fleet. For the withdrawal on demand, the policies aim on removing the wagons with the highest mileage from the train.

Case Study
For the case study, we have considered the 2020 train timetable for freight trains at the Bettemburg Eurohub Sud Terminal, including information on train rotation, the destination of outbound trains, and wagon demand. We then extended this timetable, repeating it for 20 years, to the year 2040 to understand the impact of these policies in the long-term scenario. The demand expansion has not yet been implemented but will be the subject of future research, to have more accurate data. The simulator uses a predictive model implemented in a previous study (*31*), which predicts the delay of the incoming trains based on different wagons and train features such as the weight of the wagon, the distance of the trip of the train, etc. The initial mileage of the wagon fleet has been initialized with a normal distribution based on the wagon type. The mean and the standard deviation have been calculated by extracting the data on the mileage performed by each wagon from the actual 2020 timetable. A group of 1400 wagons has been provided to the simulator: if a wagon is not used, it will not be counted in the subsequent processing of the simulation. However, if a wagon is used only once, it will be counted as having been purchased for the entire simulation.

This is a hard constraint but it is necessary to have a comparable benchmark.

RESULTS

In this section, we present the results of the simulations performed with each policy during the 2020-2040 period. Our goals are to assess to what extent the mileage limit affects rolling stocks during shunting operations and the difference in the number of wagons used to perform the simulation. Then, to further analyze this impact, we looked at the distributions in terms of operations performed on each wagon and the annual mileage performed per wagon. We then discuss the impact of applying a policy and whether this can be a first step in addressing the maintenance constraint problem for freight train operations. The data related to the *Operations on each wagon (annual)* and *Miles Performed per Wagon (km, annual)* for the *No Maintenance* Scenario have been extracted directly from the data provided by the company for the year 2021, while for the *Shunting Operations* and *Operations on wagons (annual)*, the data have been simulated with the Benchmark policy.

	NCLD	**MIN**	**Reserving**	**AVG L-S**	**Benchmark**
No Maintenance Scenario					
Shunting Ops	16434	16434	16434	16434	16434
Wagons Used	276	1199	1198	269	335
Operations on wagons (annual)					
Mean	88.68	20.29	20.29	87.46	51.84
Median	71	13	13	30	53
Variance	75.78	21.55	21.55	143.59	24
Mileage Performed per wagon (km, annual)					
Mean	27717.93	3536.2	3536.2	26145.17	28233.55
Median	21782.3	1320.9	1320.9	7774.3	23751
Variance	17272.87	6209.33	6209.33	41142.57	18507.19
Maintenance Constraint Scenario					
Shunting Ops.	18427	16850	17050	18514	20180
Wagons	1385	1335	1338	791	1450
Operations on wagons (annual)					
Mean	19.36	19.23	19.25	34.06	18.1954
Median	10	12	13	10	18
Variance	38.73	21.74	21.55	86.24	5.333884
Mileage Performed per wagon (km, annual)					
Mean	17458	15509.34	15877.81	30344.72	13696.53
Median	12490.8	12709.3	12772.5	12456.5	12091.83
Variance	33683.83	17310.18	18170.06	55399.37	9432.969
Comparison - No Maintenance vs Maintenance					
Shunting	11%	2%	4%	11%	19%
Wagons	80%	10%	10%	66%	77%
Mean Mileage Performed per wagon (km)	-37%	77%	78%	14%	-106%

TABLE 1: Performance comparison between the policies and their respective benchmark.

Table 1 presents the data on fleet management for each policy, where the analysis for each scenario will be carried out below.

No Maintenance Scenario

Shunting Ops

As can be seen, although the same number of shunting operations has been performed in each simulation, this is not valid for the same number of used wagons.

Fleet usage

The number of wagons used changes throughout the simulations because of how each policy manages the rolling stocks. For example, NCLD tends to use wagons that are already used, while AVG L-S exploits the degree of unbalance, forcing the choice on a limited group of wagons, while the other policies' criteria push them to use more and different rolling stock.

The reason why MIN and Reserving use around 1200 wagons each is because the composition of the trains can also change in terms of the number of wagons required. When this occurs, these two policies will shunt-in wagons with 0 mileage and then when these are removed, they will most likely be parked in the shunting yard and hardly ever used again. This can be explained because for MIN, given the objectives of the policy of selecting the wagon with the lowest mileage in the shunting yard, it is always discouraged to select wagons with higher mileage until new wagons are available. A similar behavior has been observed for Reserving. In addition, this type of trend is also observed in the statistically low performance in terms of annual mileage performed by the wagons of these two policies.

Mileage performed

The high mean, median, and variance of both NCLD and AVG L-S for shunting operations show their best management in terms of wagon usage for the *No-Maintenance* scenario. This can also be seen in the annual mileage data for these two policies, which are much higher compared to MIN and Reserving. Moreover, NCLD provides a more compact and resilient behavior that shows less variance when both KPIs are observed. This is a desirable feature to avoid over-usage of rolling stock, which could lead to additional maintenance. Overall, AVG L-S and NCLD perform better than the Benchmark, providing better results in all KPIs analyzed.

Maintenance Constraint Scenario

By including the maintenance constraint, important changes occur, which are described below.

Shunting Ops

The number of shunting operations performed in each scenario increases from 2% up to 19% due to the maintenance constraint. This increase can be directly attributed to maintenance constraints. It is not possible to compute exactly the number of shunting operations performed solely for maintenance reasons due to the definition of the shunting operation: if multiple rolling stocks are moved together, and within this group, there is a wagon that must be removed for maintenance operations, it is incorrect to say that this cluster has been created for maintenance. Instead, we can understand how much the maintenance constraint can affect the total number of shunting operations performed. All the policies analyzed perform a similar number of shunting operations, lower than the one provided by the Benchmark. Interestingly, while NCLD, MIN, and Reserving present similar data in almost all operations and annual mileage performed, AVG L-S stands out in all these analyzed parameters.

Fleet usage
Even though this policy presents a higher number of shunting operations performed, it also uses almost 40% less rolling stock throughout all the simulations. This shows that there is a higher number of shunting operations performed as expected, which for maintenance reasons, it can affect the overall management of the fleet.

Mileage performed
Moreover, AVG L-S also has almost twice the mean and variance with a similar median compared to the other policies. This, along with higher values in terms of kilometers performed, highlights better fleet utilization by including the maintenance constraint. Also in these two sections, all policies perform better than the Benchmark scenario.

Comparison
Looking at the Comparison, the number of used wagons increases due to fleet unavailability caused by the maintenance constraint, forcing policies to choose wagons that might be suboptimal for their criteria. It is important to emphasize how much this maintenance constraint can affect in terms of wagons used, which can increase up to 80% more for the NCLD policy and 66% for AVG L-S. Also, the average mileage per wagon falls for NCLD and Benchmark when this constraint is included, but increases for MIN, Reserving, and AVG L-S. For MIN and Reserving, the increase in the number of wagons required is almost negligible in the Maintenance-Scenario: while without unavailability, these policies can overuse some wagons and Shunt-In fresh wagons only when a demand change requests more wagons, in the Maintenance-Scenario the turnover of wagons due to maintenance mitigate the increase of the wagons and increases the mileage performed on average per wagon. From Table 1 it can be stated that more shunting operations due to maintenance constraints and higher annual mileage for each wagon can reflect better fleet management, at least for this study. On the other hand, it is not desirable to have an asymmetry for the use of the wagon fleet as can be seen in AVG L-S for both the No-Maintenance and Maintenance scenarios. Overall, it can be stated that the criteria for choosing which wagon to Shunt-In always provide better results than selecting a random wagon, and among the policies presented, the one that performs best for the analyzed KPIs is AVG L-S.

CONCLUSION
This study presents the problem of assessing and addressing the impact of maintenance constraints on freight train operations. The integration of a maintenance constraint for rolling stock shows that the quality of the solution decreases in comparison to the No-Maintenance scenario, but provides more accurate data on the long-term impact. Although this constraint proved to have a great impact in terms of Fleet Usage as expected, this methodology could become a useful tool for railway managers to improve fleet management and investments, given the low cost of its implementation . There are multiple limitations in this study that could be addressed in future research. First, The first is the t_{sin} (Shunt-In time), explained in Section Computing time to Shunt-In. This limitation can be overcome by having an RSP+TUSP model for the movement of the rolling stock as the one described in Giacco et al. (*13*). Moreover, this limitation is connected also to the choice of

the KPI analysed in this study, which could be expanded. The implementation of the RSP+TUSP tailored for a specific station could provide more precise data on more time-related KPIs, such as cancellation rates and delays in departure. This is also in the vision of the constant increase in the rail traffic. The second limitation concerns the lack of previous research studies on the topic. This forced us to make comparisons with real data, biased by COVID-19 pandemic traffic situation, without a rigorous benchmark. This could be addressed in the future by having more reliable data from the operator and testing this methodology on a larger scale. Possible future developments could be creating new policies, understanding how the Shunt-In policies can be used as a new tool to improve the overall freight management, expanding the demand to adhere to freight rail transport trends, the implementation of demand forecasting by introducing information on demand cyclicity, which can greatly improve the efficiency of the policies. In addition, a combination of policies could be studied, analyzing them from different perspectives, such as a cost analysis. Finally, a leasing constraint could be introduced into the Shunt-In problem in order to more clearly understand fleet usage and reduce the group of wagons owned, thus reducing the number of wagons needed to find a feasible solution.

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