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# Optimization of Distributed Maintenance: Design, Scheduling and Capacitated Routing Problem

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**Abstract:** This paper deals with scheduling maintenance operations for a set of geographically distributed production equipment. The problem emerges in distributed maintenance context, where a central maintenance workshop (CMW) aims to monitor and repair equipment from various production sites and schedule the associated preventive actions. A mobile maintenance workshop (MMW) transports all the resources required for the maintenance tasks to replace the equipment with spare parts provided by the CMW following the predefined schedule. This study proposes a general approach and a model to minimize the maintenance and routing costs while optimizing equipment reliability. The novelty of the proposed model is the consideration of the MMW capacity while designing and scheduling distributed maintenance. We perform several experiments based on a real-world case study to implement the model and highlight its relevance. The studied approach allows choosing the CMW position and the MMW capacity while making a trade-off between the costs and the availability of production equipment.

**Keywords:** Distributed maintenance, Maintenance scheduling, Routing optimization, Capacity constraints

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## 1. INTRODUCTION

Efficient maintenance scheduling has always led to significant amelioration in the reliability of industrial systems (Sedghi et al. 2021). It provides the chronology of maintenance tasks and assignment of a set of resources (operators, tools and spare parts). Fortunately, Industry 4.0 technologies offer the possibility to schedule and manage maintenance operations more and more smartly and in real-time (Gopalakrishnan et al. 2022). However, recent decades have experienced exponential economic growth and the development of aggressive competition for manufacturing companies (Saihi et al 2022). Thus, one of the main constraints remains the increasingly limited resources available for maintenance actions (Castro et al. 2006). An allocation problem emerges when various industrial facilities share the same maintenance resources (Zhang and Yang, 2021). It is even more emphasized in the companies where facilities are geographically distributed (Manco et al. 2022). In this case, it is complex to solve the bi-objective optimization problem concerning the schedule of maintenance operations and the routing of resources through the spread installations.

In this study, we focus on the concept of Distributed Maintenance (Simeu-Abazi and Ahmad 2011), where a Central Maintenance Workshop (CMW) pools all the maintenance resources. The CMW aims first to monitor equipment located in geographically-spread Production Sites (PS) and second to plan preventive action. A Mobile Maintenance Workshops (MMW) subject to capacity and time windows constraints ensure the routing between the CMW and the PS. The MMW thus allows transporting spare

parts and operators in the network composed by the various PS and the CMW.

Industrial applications of Distributed Maintenance arise in industries where the distance between geographically distributed equipment is not too far (Djeunang Mezafack et al. 2021). Centralization could allow reducing maintenance costs while increasing equipment availability. As an instance from the railway field, various locomotives share the same maintenance workshop for preventive actions (Hani et al. 2007). In the oil and gas industry, the location of oil platforms (onshore or offshore) sharing the same central monitoring depends on raw material sources. The centralized entity manages and performs the maintenance operations of the geographically dispersed equipment. As well as in the aircraft industry, the defective parts of aircraft are replaced directly without transporting aircraft. A centralized workshop is necessary to diagnose the origin of failures and repair them (Sanchez et al. 2020). In other applications, a third party maintains distributed facilities owned by different companies.

Several approaches are found in the literature, dealing with either the scheduling of Preventive Maintenance in CMW or the routing optimization of MMW. On the one hand, scheduling is a well-known problem in maintenance management. But, a CMW environment is more complex than a traditional job or assembly shop due to a higher level of operational uncertainty (Guide et al. 2000). On the other hand, routing optimization is a familiar problem in Operational Research. It is a combinatorial optimization and integer programming problem generally known as VRP (Vehicle Routing Problem) or TSP (Travelling Salesman

Problem). The main difficulty encountered is related to the fact that it is an NP-Hard problem (Konstantakopoulos et al. 2020). Among several variants of the VRP problem, maintenance scheduling is more related to the CVRPTW (Capacitated Vehicle Routing Problem with Time Windows).

This paper aims to combine maintenance scheduling and routing optimization. But, the literature has already addressed this problem. Indeed López-Santana et al. (2016) proposed the first modular model called CMR (Combined Maintenance and Routing). It is a two-step iterative process with a trade-off between maintenance and routing costs. But this model does not consider the capacity constraint of the MMW. Thus Vega-Figueroa et al. (2022) proposed a hybrid algorithm, and Allaham et al. (2022) defined a MILP (Mixed Integer Linear Programming) to allocate teams and tasks for each maintenance operation considering the capacity constraint of the MMW. However, these papers do not deal with both the choice of CMW position and the MMW capacity. The novelty of our contribution is to propose a general framework to design and schedule Distributed Maintenance. In addition, we improved the modular CMR model to CMCR (Combined Maintenance and Capacitated Routing).

As a reminder, after the introduction in Section 1, the problem is defined in Section 2. The next section presents the general optimization framework and the CMCR model. After that, Section 4 illustrates a case study from the railway field and, the last section concludes this work and provides some perspectives for future research.

## 2. PROBLEM DEFINITION

We consider a system with a set of  $N$  PS (Production Sites) geographically distributed over an area. Each PS has one piece of equipment subject to uncertain failures. With a schedule, an MMW (Mobile Maintenance Workshop) is responsible for transporting preventive maintenance resources (spare parts and tools) to visit the set of PS within a horizon of time, as presented in Figure 1. A CMW (Centralized Maintenance Workshops) monitors the state of each piece of equipment and stores the spare parts. The MMW starts in the CMW with a limited capacity of spare parts and visits all the PS following the optimal scheduling. When the MMW reaches a PS, the piece of equipment is replaced systematically by a spare part.

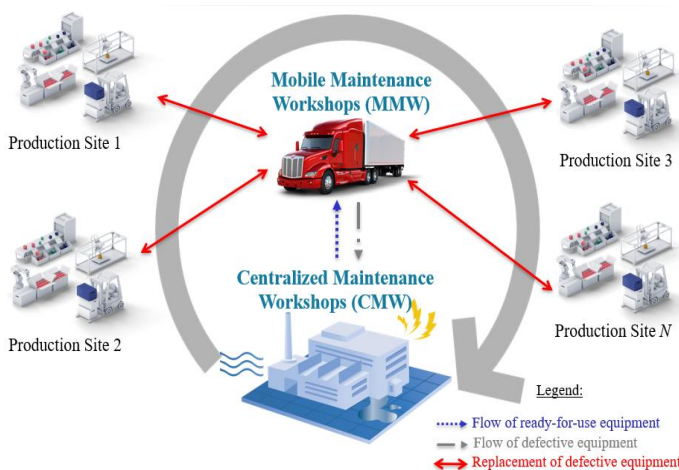


Figure 1. Distributed maintenance context

The objective is to find the optimal routing of the MMW through the PS while reducing maintenance and routing costs. The main assumptions of the problem are summarized as follows:

- The MMW is a fleet of  $m$  homogeneous vehicles, each with a limited capacity  $Q$ .
- A vehicle transports only one operator in charge of replacing a piece of equipment with a brand-new spare part.
- The travel times are deterministic and do not change over the scheduling horizon  $\tau$ .
- The CMW is a depot with an unlimited capacity.
- The PS are  $N$  geographically-spread customers, each with a single piece of equipment.
- A piece of equipment starts in "as good as new" condition and, after the replacement, it returns to "as good as new" condition.
- All the pieces of equipment are mutually independent according to their failures' behaviour. It means that the state of one piece of equipment does not disrupt those of another. Thus, we consider it is possible to optimize the frequency of preventive maintenance operations for each customer separately.
- Each customer is subject to a hard time window constraint out of which a preventive maintenance operation cannot be conducted.
- In the case of a failure, the customer waits and the following preventive maintenance operation replaces the defective equipment.

In the next section, we will present first the general framework used to optimize distributed maintenance and, second, the CMCR model for MMW visits' in detail.

## 3. OPTIMIZATION OF DISTRIBUTED MAINTENANCE

### 3.1 General framework

A Distributed Maintenance works with three main entities: MMW/vehicles, a CMW/depot and PS/customers. Figure 2 illustrates the framework, which gives an overview of the optimization process. It allows choosing the capacity of the vehicles, the position of the depot and the scheduling of the operations. Indeed, two loops allow to compare the optimal scheduling, first for different depot locations and second for various vehicles capacity. The objective is to choose the best parameters satisfying the optimal maintenance and routing costs. The first loop of positions is based on the work of Simeu-Abazi and Gascard (2020), which highlights that when the depot is near to a customer, the costs are low. The second loop of capacity tests different values of  $Q$  from  $Q_{min}$  to  $Q_{max}$ .

A core model is required to optimize the scheduling at every loop. In our study, we develop the CMCR. It is an extended version of the CMR proposed by López-Santana et al. (2016). The main contribution of our model is the integration of vehicles capacity choice. Indeed, as in the CMR, the proposed model considers as input the customers' data and the geographical location of the depot. As an innovation to the existing model, the CMCR allows the entry of vehicles capacity. The customers' data concern their geographical locations and historical statistics on their equipment failures.

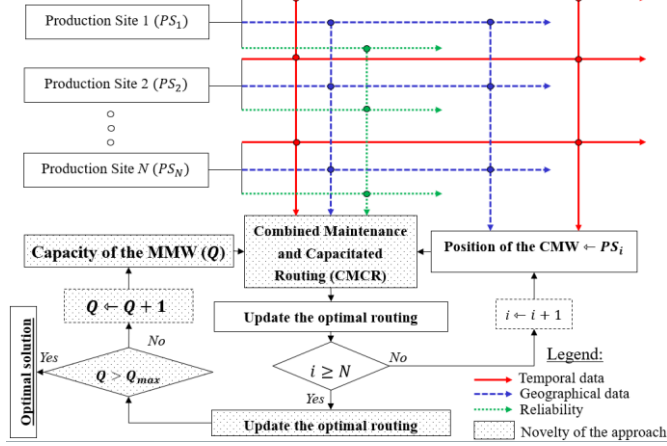


Figure 2. General framework for combining maintenance scheduling and routing optimization

### 3.2 Combined Maintenance and Capacitated Routing

The CMCR approach consists in solving two different models iteratively as presented in Figure 3:

- (1) Maintenance Model (MM): The objective is to minimize the Expected Maintenance Costs ( $E[MC]$ ). This model does not change from the CMR to CMCR and allows to find the optimal period of preventive maintenance for each piece of equipment separately. The output is the time windows for each customer at which the preventive maintenance must be carried-out within the scheduling horizon.
- (2) Capacitated Routing Model (CRM): The objective is to minimize the Expected Routing Costs ( $E[RC]$ ); this model is the main change from CMR to CMCR. It solves the well-known CVRPTW (Capacitated Vehicle Routing Problem with Time Windows) in Operational Research. In the CVRPTW, a fleet of homogeneous vehicles must service customers with known demands subject to opening hours (Konstantakopoulos et al. 2020). Based on the mathematical model used to solve this problem, the CRM proposed the optimal schedule of preventive maintenance operations.

The MM and CRM models are linked by the expected waiting time  $w_i$ <sup>1</sup> which is the period elapsing between an expected failure and the beginning of the next preventive maintenance operation. These two models loop and the sum of  $E[MC]$  and  $E[RC]$  converge to an optimal solution. The Expected Distributed Maintenance Cost is represented by:

<sup>1</sup>  $w_i$  is obtained exactly as in the CMR.

$$E[DMC] = E[MC] + E[RC]$$

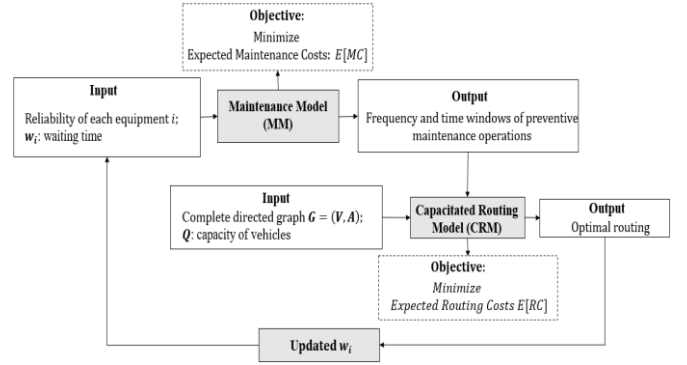


Figure 3: CMCR (Combined Maintenance and Capacitated Routing) model

In the case of higher calculation time due to the loop, it is necessary to define a tolerance interval. The optimization stops if  $E[DMC]$  doesn't exceed the bound after several iterations.

We focus now on the CRM model. We consider a complete directed graph  $G = (V, A)$ , where  $V = \{0, 1, 2, \dots, N\}$  is a set of nodes with the depot 0, and  $V_c = V \setminus \{0\}$  a subset of customers.  $A = \{(i, j) : i, j \in V\}$  represents the set of links between all pairs of nodes. The vehicles set is defined by  $K = \{1, 2, \dots, m\}$ , each with a capacity  $Q$ . Each customer  $i \in V_c$  is associated with a certain positive demand  $d_i < Q$  and an on-site service time  $T_{PMi}$ . Non-negative travel time  $t_{ij}$  and distance  $d_{ij}$  are associated to each arc  $(i, j) \in A$ .

Each customer  $i \in V_c$  has  $\eta_i$  times a preventive maintenance operation over the scheduling horizon  $\tau$ . The MM allows to obtain time windows for each operation  $[e, l]_i$ ;  $j = 1, 2, \dots, \eta_i$ . We thus consider an auxiliary grouped set of nodes  $V' = \{0, 1, 2, \dots, n\}$  where 0 is the depot and  $n = \sum_{i=1}^N \eta_i$  represents the cardinal of the set of all the preventive maintenance operations over the horizon  $\tau$ . Then, we define an auxiliary directed graph  $G' = (V', A')$ , where  $A' = \{(i', j') : i', j' \in V'\}$  represents the set of arcs. For each node  $i' \in V'$  we can find the equivalent  $i \in V$  such as  $d_{i'} = d_i$ . And, for each arc  $(i', j') \in A'$  we can find the equivalent arc  $(i, j) \in A$  such as  $t_{ij} = t_{i'j'}$  and  $d_{ij} = d_{i'j'}$ .

The problem therefore consists in solving a classical CVRPTW considering the graph  $G'$  such that:

- Each maintenance operation  $i' \in V' \setminus \{0\}$  is performed exactly once.
- A vehicle cannot transport spare parts over its capacity  $Q$ .
- Each time windows  $[e, l]_i$ ;  $i \in V \setminus \{0\}$  is equivalent to a time window  $[e_{i'}, l_{i'}]$ ;  $i' \in V' \setminus \{0\}$ .

CVRPTW is an NP-hard problem and it can be solved only for small instances of the problem. The most recent and relevant model is proposed by Borcinova (2017). Based on this classical model, we now define the Mixed-Integer Linear

Programming model (MILP) of the CRM. For the rest of the paper, we use the index  $i$  instead of  $i'$  to denote each preventive maintenance operation.

The binary decision variable  $x_{ij}$  is defined to indicate if a vehicle crosses an arc  $(i, j)$  in the optimal solution. A vehicle arrives for a service  $i$  at a time denoted by  $s_i$  and with a load  $y_i$ . The model of the CRM can be stated as follows:

*Minimize*

$$\sum_{i=0}^n \sum_{j=0}^n \text{Coef.} \left( (CD \cdot d_{ij} + CT \cdot t_{ij}) \cdot x_{ij} + m \cdot CP \right) \quad (1)$$

*Subject to*

$$-Q \cdot m \leq -\sum_{i=1}^n d_i; \quad (2)$$

$$\sum_{j=1}^n x_{0j} - m = 0; \quad (3)$$

$$\sum_{i=0}^n x_{ii} = 0; \quad (4)$$

$$\sum_{i=0, i \neq j}^n x_{ij} = 1, \quad \forall j \in V' - \{0\}; \quad (5)$$

$$\sum_{j=1, i \neq j}^n x_{ij} \leq 1, \quad \forall i \in V' - \{0\}; \quad (6)$$

$$y_i - y_j + (d_j + Q)x_{ij} \leq Q, \quad \forall i, j \in V' - \{0\}, i \neq j; \quad (7)$$

$$s_i - s_j + (T_{PM_i} + t_{ij} + \tau) \cdot x_{ij} \leq \tau, \quad \forall i, j \in V' - \{0\}, i \neq j; \quad (8)$$

$$d_i \leq y_i \leq Q, \quad \forall i \in V' - \{0\}; \quad (9)$$

$$e_i \leq s_i \leq l_i, \quad i \in V' - \{0\}; \quad (10)$$

$$x_{ij} \in \{0, 1\}, \quad \forall i, j \in V', i \neq j; \quad (11)$$

In this MILP formulation, the objective function (1) minimizes the Expected Routing Cost ( $E[RC]$ ) with:

$$\left\{ \begin{array}{l} \text{Coef: proportionnal to the capacity of the vehicles} \\ CD: \text{cost of vehicle per unit of distance} \\ CT: \text{cost of vehicle per unit of time} \\ CP: \text{purchase cost of a vehicle} \end{array} \right.$$

The constraint (2) represents the minimum number of vehicles needed to serve all the operations. The constraint (3) imposes that exactly  $m$  vehicles leave the depot. The classical flow constraints (4), (5) and (6) guarantee that each vehicle can leave the depot exactly once, and each maintenance operation is performed only once. In the constraint (7), the capacity of vehicles is stated such that the difference of a vehicle's load between two successive services  $i$  and  $j$  do not exceed the demand of  $j$ . The constraint (8) ensures that the time between two successive services  $i$  and  $j$  do not exceed  $T_{PM_i} + t_{ij}$ . The constraints (9), (10) and (11) restrict the upper and lower bounds of decision variables. In the next paragraph, we will implement the proposed model in a real-world case study.

## 4. ILLUSTRATED CASE STUDY IN RAILWAY INDUSTRY

### 4.1 Test instance

In this section, we run the CMCR model in the railway field to highlight the relevance of the proposed model. We study the case of the railway French company called SNCF (Société Nationale des Chemins de Fer). Data has been found at <https://ressources.data.sncf.com/explore/dataset/sites-de-livraison-sncf-ti-geoparts-v2/table/>. We apply the general framework proposed in Section 3.1.

- (1) Equipment: trains are considered as equipment subject to failures; preventive maintenance operations need to be scheduled every two years.
- (2) Customers: we consider nine distributed sites in a radius of 238 km of the French city of Nîmes, from which trains daily serve several railway stations. We assume that each customer has exactly one train at the departure each day, and the failure of a train is only caused by wheels degradation. The wheels are replaced within 6 days of a preventive maintenance operation and transported to the depot.
- (3) Depot: A CMW is currently located in the centre of Nîmes. It is the "Technicentre Industriel". It supplies spare parts to the vehicles.

The objective is to find the optimal location of the depot, the capacity of the vehicles and the scheduling of preventive maintenance operations. We first get the information concerning the geographical positions and historical statistics on the wheels' failures. Indeed, the matrix of distance and time of the customers' network is obtained from Google Map as illustrated in Table 1.

Table 1. Distance matrix of customers (km)

$i$	$j$									
	0	1	2	3	4	5	6	7	8	9
0	0	3	43	70	75	125	250	280	206	292
1	4	0	45	69	74	124	248	279	204	290
2	43	44	0	64	63	95	220	251	246	331
3	68	67	64	0	1	65	190	220	263	349
4	70	68	64	1	0	65	189	220	264	350
5	124	123	95	65	64	0	165	196	318	404
6	249	248	220	189	189	165	0	38	443	529
7	280	279	251	221	221	196	38	0	475	560
8	212	206	247	265	270	320	444	475	0	208
9	297	291	332	350	355	405	529	560	206	0

Table 2 presents the different health states of wheels denoted by  $T_r, r = 1, \dots, 4$ . A Weibull distribution  $W(\beta, \eta)$  describes the duration (in days) of each state. The studied wheels are currently in the state  $T_1$ .

Table 2. Expert guess of the Weibull parameters of wheels degradation in days. (Thorsten Neumann et al. 2019)

	$T_1$	$T_2$	$T_3$	$T_4$
$\beta$ (shape)	1.5	1.5	1.6	1.7

As other input to MM, the first iterative model, we have the downtime cost per time unit:  $C_w = 2500\$/j$ , and we have the service cost of replacing a wheel:  $C_{PM} = 1680\ \$$ .

The MMW has a fleet of homogeneous vehicles whose capacity needs to be optimized. The unit costs related to each vehicle are:  $CD = 0.476\ \$/km$ ,  $CT = 152\ \$/h$  and  $CP = 25000\ \$$ .

We consider 3 types of vehicles

- (1) Medium:  $Q = 4\ wheels$ ,  $Coef = 1$ ;
- (2) Heavy:  $Q = 6\ wheels$ ,  $Coef = 1.5$ ;
- (3) Extra-heavy:  $Q = 8\ wheels$ ,  $Coef = 2$ .

We choose the software Scilab 5.5.2 to implement the case study. All the tests have been run using the library “FOSSEE Optimization Toolbox” adapted for MILP. We perform the experiments on Windows 8, 64 bits machine, with an Intel(R) Core (TM) i7-10850H, CPU 2.70 GHz and 32 Go of RAM.

4.2 Results

The CMCR allows optimizing the preventive maintenance operations of geographically distributed equipment. With the case study, we have conducted experiments to highlight the relevance of the proposed model. Firstly, we considered that all the equipment are identical and at the same period of their life as presented in Table 1. We run the iterative process until reaching 10 successive iterations where the value of  $E[DMC]$  do not change to more than 1%.

We therefore run the model for all the vehicle types. In addition, we changed the position of the depot as proposed by the general framework to compare the current structure with the optimization results. It took about 16 hours to implement the case study. Thus, Figure 4 illustrates the variation of  $E[DMC]$ , as a function of the vehicle type and the depot position. It can be observed that for an unlimited capacity, the current position of the depot denoted by 0 is the third most cost-effective. With the capacity constraint for this scenario, the medium vehicle is the best choice. And, if the depot were near customer number 6, the cost would be less than the current. For this scenario, the capacity constraint allows reducing the cost to more than 5.6%. Since the capacity is considered unlimited, the company needs to buy a more expensive vehicle covering all the equipment demand. But, with the proposed model, an optimized routing can be obtained despite the limited capacity.

Secondly, to explore the influence of the equipment state in the  $E[DMC]$ , we run the model for the different periods of the wheel’s life (from  $T_1$  to  $T_4$ ). Figure 5 shows the evolution of the total cost versus different depot positions while using medium vehicles. It is clear that for these scenarios, the more equipment is old, the higher the total cost is. For example, if the depot is in the current position, in period  $T_1$ , the distributed maintenance will cost 547\$/day while costing 649\$/day in  $T_4$ . But,  $E[DMC]$  does not change too much for a

chosen wheels’ state. As an instance, for  $T_1$ , the minimum value of  $E[DMC]$  is 545\$/day and, its maximum value is 549\$/day. For  $T_2$ , the minimum value of  $E[DMC]$  is 595\$/day while its maximum value is 602\$/day. It could be justified by the fact that according to a given state of wheels, the frequency of preventive maintenance operations is too low to highlight the influence of the depot position. Indeed, at state  $T_1$  for example, a wheel need about 24 preventive operations performed within 2 years as illustrated in Figure 6. It represents about 1 operation each month.

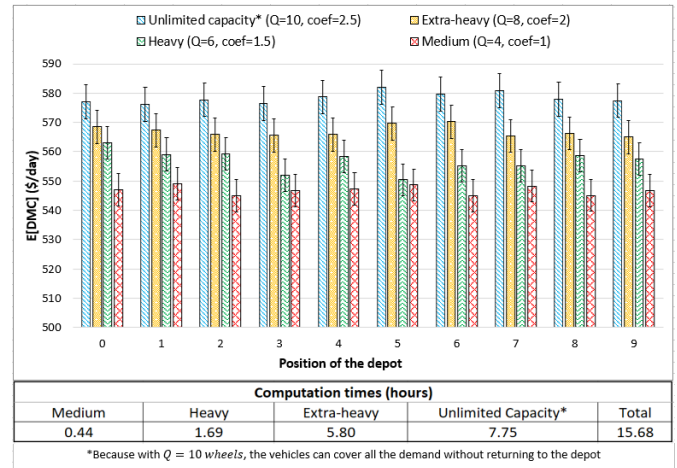


Figure 4. Costs versus vehicles’ capacity and depot’s position

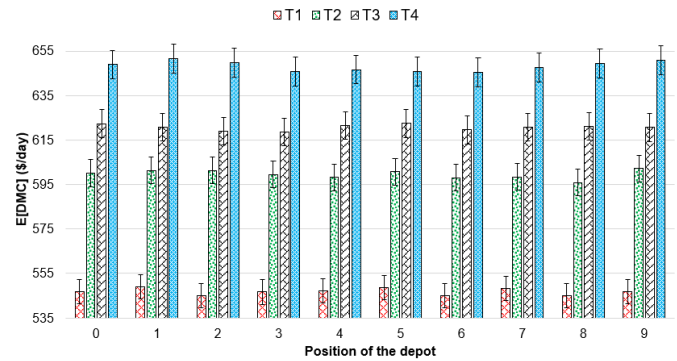


Figure 5. Costs versus wheels’ degradation and depot’s position

Finally, the medium vehicles are the best MMW’s choice for this case study. However, the results do not well highlight the influence of the depot position. Furthermore, equipment the frequency of failures is higher could solve this problem. For example, it could be the wheels in a more degraded state. Or, by considering more production sites, the numbers of operations may increase.

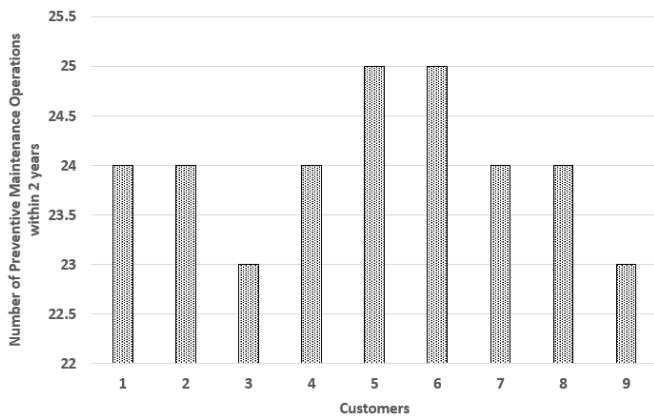


Figure 6. Number of preventive maintenance operations to be performed within the schedule horizon of time.

## 5. CONCLUSION

This paper addresses the combination of maintenance scheduling and routing optimization. We focus on a distributed maintenance context where a set of geographically dispersed production sites need to be visited frequently for preventive maintenance operations. We proposed a novel model to consider the capacity constraints of the vehicles transporting spare parts and operators.

We made some assumptions to fit the problem with the known approach of Operational Research and Maintenance Management. The main contribution of this work is the reduction of maintenance and routing costs while optimizing the scheduling of preventive maintenance operations. We implemented the proposed model in a case study from the railway field and showed an improvement of more than 5.6% in the expected costs.

Future research based on this work could remove some assumptions in the modelling of the distributed maintenance system. We assumed that defective equipment in a production site must always wait for the following preventive maintenance operation for the replacement. [However, this equipment may require an emergency repair. Thus, re-scheduling could be studied to reflect the real-world process.](#) In addition, it is necessary to consider the environmental issues of the proposed model since the transport sector is a contributor to CO<sub>2</sub> emissions. Circular strategies such as remanufacturing, for example, could allow reducing the carbon footprint of each defective piece of equipment.

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