An approach for mastering Carbon Footprint in the context of Distributed Maintenance

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Rony Arsène DJEUNANG MEZAFACK*, Zineb SIMEU-ABAZI**, Maria DI MASCOLO***
Grenoble Alpes, CNRS, Grenoble INP, G-SCOP, 38000 Grenoble, France
*(e-mail: rony.djeunang-mezafack@grenoble-inp.fr).
**(e-mail: zineb.simeu-abazi@grenoble-inp.fr)
*** (e-mail: maria.di-mascolo@grenoble-inp.fr)

***Abstract*—This paper deals with the carbon footprint of distributed maintenance operations. It concerns the maintenance scheduling of a set of geographically distributed production sites where pieces of equipment are subject to failure. Their health state is monitored by a central maintenance workshop (CMW), which plans the corresponding preventive maintenance (PM) tasks and repairs defective equipment. A mobile maintenance workshop (MMW) transports all the resources necessary to maintain each piece of equipment, following the predefined schedule. This study aims to propose an approach to reducing CO_2 emissions of the MMW routing. The model allows choosing the optimal position of the CMW and the capacity of vehicles, both satisfying a low cost and a low carbon footprint. We conduct several experiments from a real-world case study and European Union (EU) regulation. The results show a trade-off between operational profitability and strategic sustainability.**

Keywords— Distributed maintenance; Maintenance scheduling; Routing optimization; Carbon footprint

I. INTRODUCTION

Every manufacturing systems are subject to failure. Their reliability and availability depend strongly on the quality of Maintenance Management [1]. Thus, production assets require monitoring and scheduling the associated maintenance actions (preventive and corrective). Fortunately, the evolution of technologies has led to an Industry 4.0 where managers can predict failures and conduct maintenance operations remotely and in real-time [2]. However, they remain confronted with the limitation of budget and resources dedicated to maintenance [3]. It is even more complicated when a single company manage the maintenance of geographically dispersed Production Sites (PS) [4]. One solution to reduce embedded costs consists in sharing all the resources (spare parts, operators and tools) in a Central Maintenance Workshop (CMW) [5], also known as a repair shop [6]. The first concept implementing this approach is called Distributed Maintenance [7].

This paper studies the reduction of CO_2 emission in Distributed Maintenance. Indeed, it concerns the Preventive Maintenance (PM) scheduling of geographically spread PS in which the distances to each other are not too high. A Mobile Maintenance Workshop (MMW) transports the resources from the CMW to the PS, where pieces of manufacturing equipment are subject to failure. Following an optimal schedule, the MMW progressively replace each piece of equipment with spare parts to prevent expected collapse. However, one of the main contributors to global CO_2 emission is the transport sector [8]. It represented about 20% in 2021 [9]. Hence, Distributed Maintenance faces environmental issues. The objective is then to reduce carbon footprint while optimizing the routing of the MMW.

Several approaches are found in the literature, dealing with either the scheduling in Maintenance Management [10] or the routing in Operational Research [11]. Then, the existing contributions allow optimizing the visits of the MMW considering the constraints related to the uncertain equipment state and the capacity constraint of the MMW. However, these models don't embed the optimization of carbon footprint. From this gap, this paper provides an improved model called SMCR (Sustainable Maintenance and Capacitated Routing). The novelty of the approach is to consider the CO_2 emissions mainly related to the transport of resources. Thus, we state two research questions as follow:

- In the context of Distributed Maintenance, what are the elements that generate CO_2 emissions?
- How to reduce the carbon footprint of the MMW?

This document is organized into six sections. After an introduction to the context of this work in section 1, section 2 is devoted to the literature review. Section 3 defines the problem and Section 4 presents in-depth the proposed solution. Experiments are conducted in Section 4 to explore the relevance of the study approach. The last section contains our conclusion and future research work.

II. LITTERATURE REVIEW

Recent technological advances, such as Wireless Sensor, Ad-hoc Networks, Internet of Things, Cloud Computing, multi-agent systems and so on, led to the emergence of architectures allowing the management of several smart production assets geographically dispersed [12]. Therefore, Distributed Maintenance was first clearly defined in 2014 [7]. Indeed, three main steps allow its implementation: first, modelling and sizing of a CMW, whose systematic literature review has been

conducted in 2021 [6]. The main difficulty remains optimizing the CMW location [13], increasing with the number of PS to serve and all the constraints embedded.

It is secondly necessary to define the optimal maintenance policy for distributed PS. Among the few studies dealing with the scheduling of distributed maintenance, [14] proposed in 2016 a model for a fixed frequency of Preventive Maintenance operations while reducing the occurrence of failures. However, the stochastic behaviour of equipment failures and their degradation require a more intelligent schedule. Thus, [15] proposed in 2018 a bi-objective model based on predictive knowledge and residual-useful life of production equipment. Another recent paper [16] studied a dynamic approach to identify critical facilities and smartly determine components that could be replaced preventively. However, a major barrier faced by the authors is the combination of maintenance scheduling and the routing optimization of the MMW.

Indeed, the third step of Distributed Maintenance consists to schedule the routing of the MMW considering the constraints of capacity, costs and maintenance policy. Various recent studies contribute to solving this problem. For instance, [17] proposed a hybrid algorithm combining the optimal choice of the PM frequency and the routing of the vehicles. [18] define a MILP (Mixed Integer Linear Programming) to allocate teams and tasks for each PM operation. In addition, a routing problem is an NP-Hard problem [19]. [20] deals with the computation time to solve the MILP. Unfortunately, all these approaches do not embed the environmental issues due to the transport of resources for maintenance actions.

MMW generally consist of vehicles that transport spare parts, tools and operators. It produces CO_2, which contributes to the rise in the global average temperature [21]. Carbon footprint [22] is a widely used term to measure the environmental impact of transport activities. Different methods and regulations exist to estimate it depending on the countries [23]. In this study, we will focus on the low carbon practices of the European Union (EU) [24]. In 2018, the transport sector represented 29% of the total CO_2 emissions in the EU, against 10% in China and 36% in the USA [25].

III. PROBLEM DEFINITION

We study a system with a set of N Production Sites (PS) geographically dispersed over an area. We consider each PS has one piece of equipment subject to uncertain failures. A Mobile Maintenance Workshop (MMW) aims to transport preventive maintenance resources (spare parts and tools). With a schedule, the set of PS is visited within a horizon of time, as presented in Figure 1. A Centralized Maintenance Workshop (CMW) stores the spare parts and monitors the health state of each piece of equipment. The MMW starts in the CMW with a limited capacity of spare parts and visits all the PS. When the MMW reaches a PS, the piece of equipment is replaced systematically by a spare part. The goal is to optimize the routing of the MMW through the PS while reducing maintenance costs, routing costs and carbon footprint.

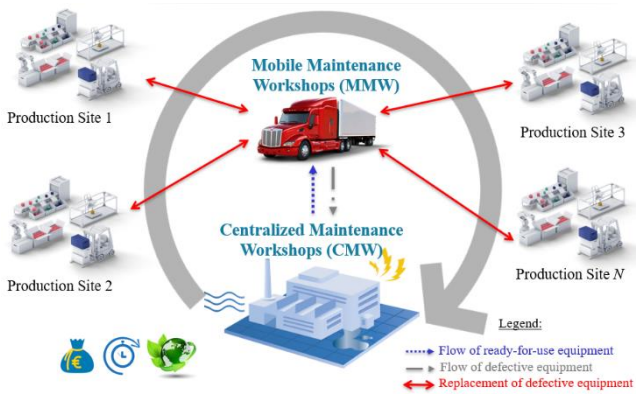

Fig. 1. Distributed maintenance context.

The main assumptions of the problem are summarized as follows:

1. The MMW is a fleet of m homogeneous vehicles, each with a limited capacity Q.
2. A vehicle travels with only one operator in charge of replacing a piece of equipment with a brand-new spare part.
3. The travel times do not change over the scheduling horizon τ.
4. The CMW has unlimited capacity.
5. A piece of equipment is considered not subject to degradation.
6. The health state of one piece of equipment does not disrupt that of another one. Thus, it is possible to optimize the frequency of preventive maintenance (PM) operations for each piece of equipment separately.
7. Each PM operation must be conducted in a hard time window.
8. When a failure occurs, the customer waits and the following PM operation allows to replace the defective equipment.

In the next section, we propose a model called SMCR to solve the scheduling and routing problem in the context of Distributed Maintenance.

IV. OPTIMIZATION OF DISTRIBUTED MAINTENANCE

Generally, it consists in choosing the vehicles' capacity and the position of the depot while optimizing the schedule of PM operations. The novelty of our study is the consideration of CO_2 emissions. Thus, we use the general framework proposed by [26] and extend the core model from CMCR (Combined Maintenance and Capacitated Routing) to SMCR. Indeed, as presented in Figure 2, the input of SMCR is customers' data concerning their geographical locations and equipment failures laws. The SMCR model consists in solving two different sub-models iteratively:

(1) Maintenance Model (MM): The objective is to minimize the Expected Maintenance Costs (E[MC]). This sub-model is first developed by [14]. It allows optimizing the frequency of PM operations for each piece of equipment separately. It provides optimal time windows for each customer within the scheduling horizon.

(2) Sustainable Routing Model (SRM): The objective of this sub-model is to minimize the Expected Routing Costs (E[RC]). It is the prime change from CMCR to SMCR. It solves a CVRPTW (Capacitated Vehicle Routing Problem with Time Windows), well known in Operational Research. In the CVRPTW, a fleet of homogeneous vehicles is in charge of serving customers with known demands subject to opening hours [11]. The proposed SRM is a mathematical model used to solve the routing problem and carbon footprint improvement.

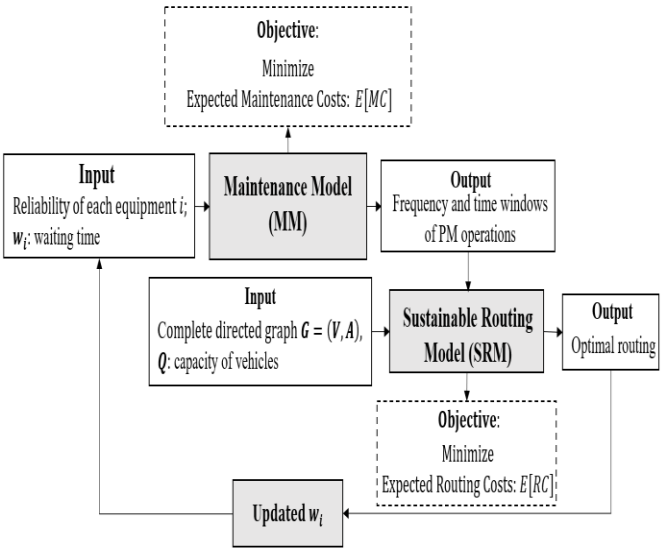

Fig. 2. SMCR Model

The MM and SRM sub-models are linked by the expected waiting time w_i[1] which is the period elapsing between an expected failure and the beginning of the next PM operation.

These two models loop and the sum of $E[MC]$ and $E[RC]$ converge[2] to an optimal solution. The Expected Distributed Maintenance Cost is represented by:

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

We go now more in-depth in the SRM model. Let's 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 $V_c = V\backslash\{0\}$ a subset of customers. $A = \{(i,j): i,j \in V\}$ denotes the set of links between all pairs of nodes. The vehicles set is represented by $K = \{1,2, \dots, m\}$, each with a capacity Q. Each customer $i \in V_c$ has 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 $(i,j) \in A$.

The MM allows to obtain time windows for each operation $[e_j, l_j]_i$; $j = 1,2, \dots, \eta_i$; where η_i is the total number of preventive maintenance operations over the scheduling horizon τ for each customer $i \in V_c$. 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 τ. 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 $i' \in V'\backslash\{0\}$ is performed exactly once.
- A vehicle cannot transport spare parts over its capacity Q.
- Each time windows $[e_j, l_j]_i$; $i \in V\backslash\{0\}$ is equivalent to a time window $[e_{i'}, l_{i'}]$; $i' \in V'\backslash\{0\}$.

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 [27]. Based on this classical model, we now define the Mixed-Integer Linear Programming model (MILP) of the SRM. For the rest of the paper, we use the index i instead of i' to denote each PM 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 SRM model is composed of a function E[RC] and constraints.

$$E[RC] = \sum_{i=0}^{n} \sum_{j=0}^{n} \left(Coef.CD + \frac{CT}{V}\right).d_{ij}.x_{ij} + Coef.CP.m \quad (1)$$

$Where$:

$$\begin{cases} Coef: proportionnal\ to\ the\ capacity\ of\ the\ vehicles \\ CD: cost\ of\ vehicle\ per\ unit\ of\ distance\ (\$/km) \\ CT: cost\ of\ vehicle\ per\ unit\ of\ time\ (\$/h) \\ CP: purchase\ cost\ of\ a\ vehicle\ (\$) \\ V: average\ speed\ of\ vehicles\ (km/h) \end{cases}$$

[1] w_i is obtained exactly as in [14].

[2] It is necessary to define a tolerance interval for convergence. The optimization stops if *E[DMC]* doesn't exceed the bound after several iterations.

It is a question to adapt the objective function according to the European strategies for low-emission transport [28]. Indeed, two formulas allow to evaluate the expected carbon footprint:

$$E[CF]_1 = \sum_{i=0}^{n}\sum_{j=0}^{n} EF.CR.d_{ij}.x_{ij} \quad (2)$$

$$E[CF]_2 = \sum_{i=0}^{n}\sum_{j=0}^{n} EF.CR.\frac{y_i}{Q}.d_{ij}.x_{ij} \quad (3)$$

$$Where: \begin{cases} EF: Emission\ Factor\ (kgCO2e/l) \\ CR: Comsumption\ Rate\ (l/km) \end{cases}$$

Formula (2) is used when the vehicles and production equipment are owned by the same company and Formula (3) otherwise.

From the equations (1), (2) we establish a new objective function that considers both the routing costs and the CO_2 emissions as follow:

$$Minimize$$

$$(1-\boldsymbol{\varepsilon}).E[RC] + \boldsymbol{\varepsilon}.EC.E[CF]_1 \quad (4)$$

$$Subject\ to$$

$$-Q.m \leq -\sum_{i=1}^{n} d_i\ ; \ (5)$$

$$\sum_{j=1}^{n} x_{0j} - m = 0\ ; \ (6)$$

$$\sum_{i=0}^{n} x_{ii} = 0\ ; (7)$$

$$\sum_{i=0,i\neq j}^{n} x_{ij} = 1,\ \forall j \in V' - \{0\}\ ; \ (8)$$

$$\sum_{j=1,i\neq j}^{n} x_{ij} \leq 1,\ \forall i \in V' - \{0\}\ ; (9)$$

$$y_i - y_j + (d_j + Q)x_{ij} \leq Q,\ \forall i,j \in V' - \{0\}, i \neq j; (10)$$

$$s_i - s_j + \left(T_{PM_i} + t_{ij} + \tau\right).x_{ij} \leq \tau\ , \quad \forall i,j \in V' - \{0\}, i \neq j\ ; (11)$$

$$d_i \leq y_i \leq Q,\ \forall i \in V' - \{0\}\ ; (12)$$

$$e_i \leq s_i \leq l_i, i \in V' - \{0\}\ ; \ (13)$$

$$x_{ij} \in \{0,1\},\ \forall i,j \in V', i \neq j\ ; \ (14)$$

In this MILP formulation, the objective function (4) embeds a variable $\varepsilon \in [0,1]$ which denotes the trade-off between the minimal routing costs and the minimal carbon footprint. EC represents the emission cost ($\$/kgCO2e$). The constraint (5) determines the minimum number of vehicles needed to serve all the operations. The constraint (6) imposes that exactly m vehicles leave the depot. The classical flow constraints (7), (8) and (9) guarantee that each vehicle can leave the depot exactly once, and each maintenance operation is performed only once. In the constraint (10), 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 (11) ensures that the time between two successive services i and j do not exceed $T_{PM_i} + t_{ij}$. The constraints (12), (13) and (14) 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.

V. ILLUSTRATED CASE STUDY IN OIL AND GAS INDUSTRY

a. Test instance

In this section, we run the SMCR in the oil and gas field to highlight the relevance of the proposed model.

(1) Equipment: we study the case of onshore pumps.

(2) Customers: we consider ten distributed pumping stations in a radius of 300 km. The matrix of distances $[d_{ij}]$ is represented by the Appendix 1.

(3) We assume that each customer has exactly one pump subject to uncertain failures. A pump is systematically replaced within a PM operation and transported to the depot.

The objective is to find the optimal location of the depot, the capacity of the vehicles and the scheduling of PM operations. We first get data on pump failures and operational costs [14] (Appendix 2 for details).

The MMW has a fleet of homogeneous vehicles whose capacity needs to be optimized. The unit costs related to each vehicle are: $CD = 0.476\$/km$, $CT = 60\$/h$ and $CP = 12{,}000\$$. We consider 3 types of vehicles with an average speed of $60km/h$ as shown in Table 2. $EC = 0.145\$/kgCO2e$ [29]

TABLE 2. TYPES OF VEHICLES

Vehicles	$Coef$	Q	$Power$ (ch)	EF ($kgCO_2/l$)	CR (l/km)
Medium	1.0	4	350	3.16	0.087
Heavy	1.5	6	525	3.16	0.210
Extra-heavy	2.0	8	700	3.16	0.330

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.

b. Results

The SMCR reduces the carbon footprint of PM operations for geographically distributed equipment. In this case study, several experiments explore the benefits of the proposed model. Indeed, we have executed the proposed iterative process until reaching ten successive iterations where the value of $E[DMC]$ does not change by more than 1%. Five instances of the solution can be considered by varying the parameter $\varepsilon \in [0,1]$ as shown in Table 3.

Therefore, each solution instance is made to choose the right type of vehicle and the best depot position that satisfies the

lowest cost $E[DMC]$. For example, Figure 3 presents the results obtained for SMCR-1 ($\varepsilon = 1$). Indeed, it can be observed that when the depot is near customer 8, the costs are the lowest with a heavy vehicle ($131\$/h$). Figure 4 represents as instance, the corresponding carbon footprint $E[CF]_1$ ($8.19\ kgCO2e/h$).

TABLE 3. INSTANCES OF SOLUTION AVAILABLE

Instance	**1**	**2**	**3**	**4**	**5**
$\boldsymbol{\varepsilon}$	0	1	0.75	0.5	0.25
Model	CMCR	SMCR-1	SMCR-0.75	SMCR-0.5	SMCR-0.25

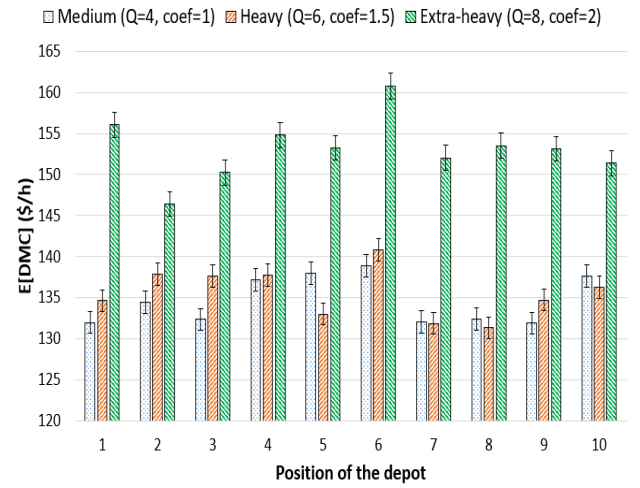

Fig. 3. Expected Ditributed Maintenance Cost for SMCR-1

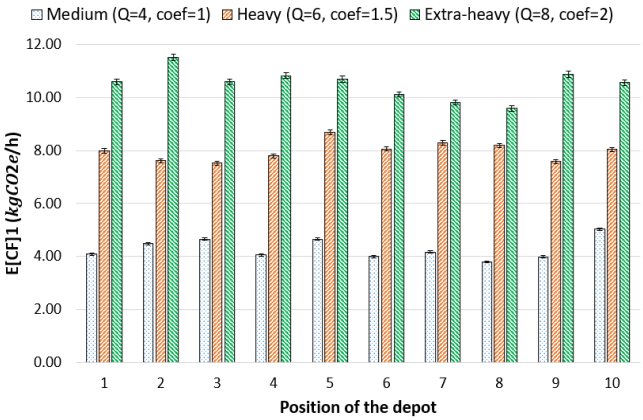

Fig. 4. Expected Carbon Footprint for SMCR-1

To better present the results, Table 4 only represents the best parameters for each instance of the solution. Obviously, the existing CMCR model provides the best $E[DMC]$. But, its carbon footprint compared to the others is the worst. In fact, ε allows the reduction of $E[CF]_1$ by 48% and $E[CF]_2$ by 47%. However, the penalty for obtaining a lower emission of CO_2 only represents 2% of $E[DMC]$. It can be balanced if the company has to pay a carbon tax.

In addition, by converting $E[CF]_1$ into $gCO2e/km$, we can compare the results to the EU target for the period of 2020-2024 [30], as presented in Figure 5. It can be observed that the proposed model allows dropping the emission of CO_2 to less than $95gCO2e/km$.

TABLE 4. RESULTS FOR EACH INSTANCE OF PROPOSED SOLUTION

	CMCR	**SMCR-1**	**SMCR-0.75**	**SMCR-0.5**	**SMCR-0.25**
E[DMC] ($/h)	127	131	130	130	129
E[CF]₁ ($kgCO2e$/h)	8.40	8.19	8.35	4.41	4.66
E[CF]₂ ($kgCO2e$/h)	4.64	4.53	4.46	2.46	2.48
Position of the depot	1	8	9	9	8
Capacity of vehicles	Heavy	Heavy	Heavy	Medium	Medium
Computation time (h)	2.41	4.73	5.91	7.45	6.32

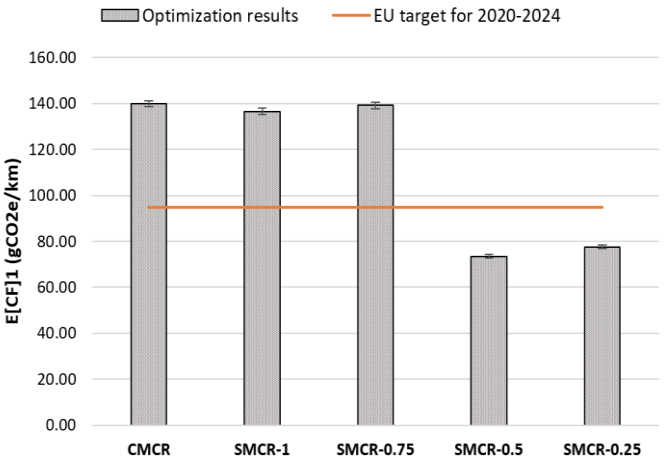

Fig. 5. Carbon footprint overview

VI. CONCLUSION

This paper tackled the problem of carbon footprint in the distributed maintenance context. We considered a set of geographically dispersed production sites where equipment is subject to failures. PM operations need to be performed in a horizon of time to ensure the reliability of facilities. We proposed a model to reduce the CO_2 emission of the vehicles transporting spare parts, operators and tools, without degrading too much the maintenance cost.

Several experiments have been run to explore the relevance of the proposed model. The carbon footprint is reduced by more than 47%, while the costs could increase by less than 2%. However, in the case where the concerned company has to pay taxes for CO_2 emissions, the costs could be balanced. Furthermore, according to the EU low carbon goals for the period of 2020-2024, our study shows that the distributed maintenance concept fits the expectation (less than $95gCO2e/km$).

However, we assumed that each production site has exactly one piece of equipment. But in most industries, various pieces of equipment are handled in the same place. Future research based on this work could extend this possibility. Furthermore, it could be interesting to consider some cases where uncertain failure occurs while implementing the optimal schedule of PM operations. In addition, it can be more realistic considering the entire life cycle of production equipment. Their end of life could be studied through circular strategies such as remanufacturing or recycling. Another extension could be the study of electric vehicles for transportation instead of thermal, with the related autonomy problem.

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APPENDIX 1. DISTANCE MATRIX OF CUSTOMERS (HOURS)

i	*j*										
	0	1	2	3	4	5	6	7	8	9	10
0	0	258	136	179	164	327	211	191	176	191	326
1	258	0	207	101	146	69	230	85	111	86	176
2	136	207	0	184	62	272	76	185	189	121	204
3	179	101	184	0	141	161	237	16	11	99	249
4	164	146	62	141	0	210	96	138	149	60	162
5	327	69	272	161	210	0	284	145	170	152	192
6	211	230	76	237	96	284	0	234	245	150	162
7	191	85	185	16	138	145	234	0	26	91	237
8	176	111	189	11	149	170	245	26	0	109	260
9	191	86	121	99	60	152	150	91	109	0	157
10	326	176	204	249	162	192	162	237	260	157	0

APPENDIX 2. DATA ON PUMP'S FAILURES

i	C_{PMi}[a]	T_{PMi}[a]	C_{wi}[a]	$f_i(t)$[b]
1	183	9	15	*N*(45,4)
2	121	5	14	*N*(54,4.5)
3	193	6	19	*W*(66,3.5)
4	156	8	14	*W*(100,3.5)
5	138	8	13	*W*(63,3.5)
6	194	10	17	*N*(44,4.4)
7	163	9	15	*W*(84,3.5)
8	100	9	12	*N*(78,7)
9	193	6	13	*N*(96,8.728)
10	105	10	18	*N*(75,6.819)

a. C_{PMi}: service cost of replacing a pump; T_{PMi}: time necessary to replace a pump; C_{wi}: downtime cost per time unit

b. $N(\mu, \sigma)$ denotes the Normal probability density function with mean μ and standard deviation σ; and $W(\lambda, k)$ denotes the Weibull probability density function with scale parameter λ and shape parameter k.