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Distributed Maintenance: Design, Scheduling and Capacitated Routing Problem*

Rony A. DJEUNANG MEZAFACK, Zineb SIMEU-ABAZI, Maria DI MASCOLO

Abstract—This paper addresses the scheduling maintenance operations for a set of geographically dispersed production equipment. We consider various equipment subject to uncertain failures that need to be monitored and repaired by a central maintenance workshop (CMW). We focus on the associated preventive maintenance actions, which require optimal scheduling. A mobile maintenance workshop (MMW) aims to transport all the resources to systematically replace the equipment with spare parts provided by the CMW following the predefined schedule. We propose a general framework and a model to minimize the maintenance and routing costs while optimizing equipment reliability. The novelty of the proposed model is the reduction of computation time through the proposition of heuristic methods while considering capacity constraints and various types of equipment. We perform several instances of problems in the oil and gas field. The studied approach optimizes the location of the CMW and the capacity of the MMW, solving the NP-Hard Problem.

I. INTRODUCTION

Manufacturing systems reliability and availability depend mainly on the quality of maintenance management [1]. In general, the aim is to monitor production assets, schedule maintenance actions and conduct various preventive or corrective tasks. Fortunately, industry 4.0 technologies allow anticipating the failures of production equipment. Therefore, operations are becoming more and more smart and remote [2]. But it is well known that the major constraint faced by managers remains the limited budget dedicated to the maintenance [3]. One of the solutions to reduce costs consists of sharing the same resources (spare parts, operators and tools) for different facilities. However, an allocation problem arises since the schedule of several maintenance tasks depends strongly on the availability of resources [4]. It is even more accentuated when the facilities are geographically distributed [5].

In this paper, we study the implementation of Distributed Maintenance [6]. The concept consists of gathering all the resources in a central maintenance workshop (CMW), also known as repair shop [7]. A mobile maintenance workshop (MMW) is in charge of the routing between the CMW and geographically spread production sites (PS), where pieces of manufacturing equipment are subject to failures. The objective is to schedule preventive actions for each PS, optimize the MMW preventive visits and restore defective equipment in the CMW as soon as possible.

Industrial applications of Distributed Maintenance are emerging in industries where the distance between geographically dispersed equipment is not too great [7]. Centralization could

reduce maintenance costs while increasing equipment availability [8]. For example, several locomotives share the same maintenance workshop for preventive actions in the railway sector [9]. In the oil and gas industry, the location of oil platforms (onshore or offshore) sharing the same central control depends on the sources of raw materials. The centralized entity manages and carries out maintenance operations on geographically dispersed equipment. As well as in the aviation industry, defective aircraft parts are replaced directly without transporting the aircraft. A centralized workshop is needed to diagnose the origin of faults and repair them [10]. In other applications, a third party maintains distributed installations of different companies.

This paper aims to optimize maintenance costs while reducing downtime of geographically dispersed equipment throughout Distributed Maintenance. The literature provides several studies dealing with this objective. But, one of the main difficulties faced by the authors is the combination of maintenance scheduling of PS and routing optimization of MMW. Indeed, López-Santana et al. (2016) proposed one of the first modular models called CMR (Combined Maintenance and Routing) [11]. It is a two-step iterative process that makes a balance between maintenance and routing costs. But this model does not consider the capacity constraint of transportation between the PS with equipment to be maintained. Hence, Vega-Figueroa et al. (2022) proposed a hybrid algorithm [16] and Allaham et al. (2022) defined a MILP (Mixed Integer Linear Programming) [17] to allocate teams and tasks for each maintenance operation considering the capacity constraint of spare parts. Djeunang Mezafack et al. (2022) propose a MILP and a general framework called CMCR (Combined Maintenance and Capacitated Routing) [18] to choose the capacity of the MMW and the location of the CMW. However, all these approaches require exponential computation time since they tackle an NP-Hard problem. Thus, the existing models only allow solving small instances of the problem. From this gap, this paper provides an improved model called OMCR (Optimized Maintenance and Capacitated Routing). The novelty of the approach is to reduce the complexity of the optimization algorithm while considering the capacity constraints of the MMW and various types of equipment under Distributed Maintenance. Thus, we state two research questions as follow:

- How to implement Distributed Maintenance with diverse types of equipment?
- How to optimize the capacitated routing of the MMW with a low computation time?

The paper is structured into five sections. Following an introduction about the context of this work in section 1, section

2 is dedicated to the problem definition. The optimization of Distributed Maintenance is presented in section 3. Section 4 conducts experiments to highlight the relevance of the proposed approach. The last section contains our conclusion and future research perspectives.

II. PROBLEM DEFINITION

We consider a system with a set of N Production Sites (PS) geographically distributed over an area. Each PS has one piece of equipment subject to uncertain failures. With a schedule, a Mobile Maintenance Workshop (MMW) 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 Centralized Maintenance Workshops (CMW) 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.

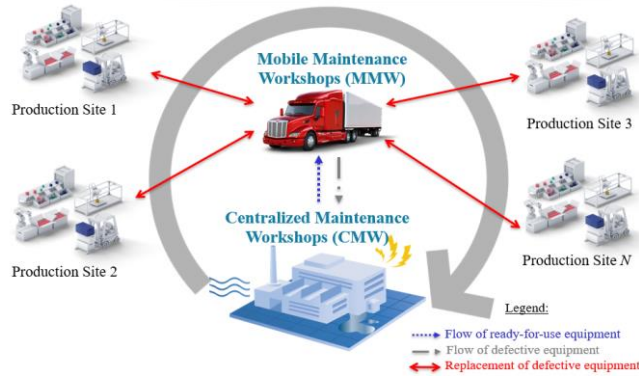


Figure 1. Distributed Maintenance context [18].

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:

1. The MMW is a fleet of m homogeneous vehicles, each with a limited capacity Q .
2. A vehicle transports only one operator in charge of replacing a piece of equipment with a brand-new spare part.
3. The travel times are deterministic and do not change over the scheduling horizon τ .
4. The CMW is a depot with an unlimited capacity.
5. The PS are N geographically-spread customers, each with a single piece of equipment.
6. A piece of equipment starts in "As Good As New" condition and, after the replacement, it returns to "As Good As New" condition.

7. 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 (PM) operations for each customer separately.

8. Each customer is subject to a hard time window constraint out of which a PM operation cannot be conducted.

9. In the case of a failure, the customer waits and the following PM operation replaces the defective equipment.

In the next section, we will present, first, the general framework used to optimize Distributed Maintenance and, second, the OMCR model in detail.

III. OPTIMIZATION OF DISTRIBUTED MAINTENANCE

A. 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, generally, two loops allow to compare the optimal scheduling, first for different depot locations and second for various vehicles capacity [18]. The goal is to choose the best parameters satisfying the optimal maintenance and routing costs.

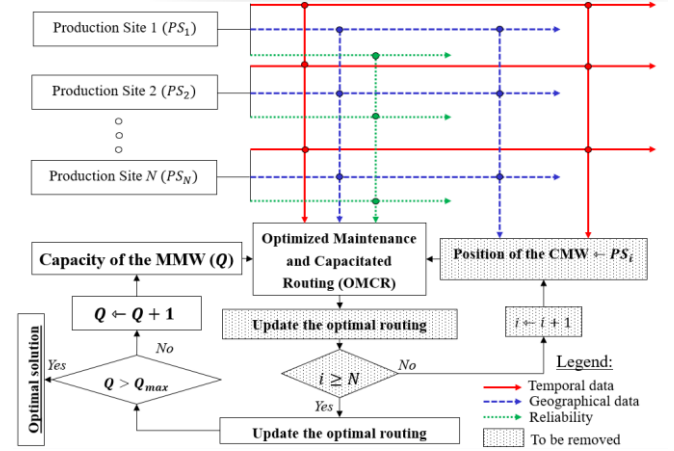


Figure 2. General framework with the part to be removed after integrating the OMCR model.

The position first loop considers the routing cost is low when the depot CMW is close to a customer PS_i , $i = 1, \dots, N$ [12]. The second loop of capacity tests different values of Q from Q_{min} to Q_{max} . But, this general process requires excessive computation time due to these two loops. However, after integrating the new OMCR model into the framework, the loop concerning the position of the depot is no more necessary.

It could therefore reduce the computation time. Hence, the core model, OMCR, is an extended version of the CMCR [18]. The main contribution of our model is the integration of the depot position choice in the optimization model reducing computation time. Indeed, as in the CMCR, the proposed model considers as input the capacity of vehicles and data of customers. It concerns their geographical locations and historical statistics on their equipment failures. As an innovation, OMCR enables a suitable position for the depot to be found automatically without going through the loop of different locations.

B. Optimized Maintenance and Capacitated Routing

The OMCR model consists in solving two different sub-models iteratively as presented in Figure 3:

- (1) **Maintenance Model (MM):** The objective is to minimize the Expected Maintenance Costs ($E[MC]$). This sub-model does not change from the CMR to OMCR and allows to find the optimal period of PM for each piece of equipment separately. The output is the time windows for each customer at which the PM must be carried-out within the scheduling horizon.
- (2) **Heuristic Routing Model (HRM):** The objective is to minimize the Expected Routing Costs ($E[RC]$); this model is the first main change from CMR to OMCR. 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 [13]. Based on the mathematical model used to solve this problem, the HRM proposed the optimal schedule of PM operations.

The MM and HRM sub-models are linked first by the position of the depot, which is the second and last main change in the model. Indeed, we consider that the depot is located at the barycentre of the customers weighted by each number of PM operations η_i obtained from the MM sub-model. In addition, the two 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 $E[RC]$ converge² to an optimal solution. The Expected Distributed Maintenance Cost is represented by:

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

We focus now on the HRM sub-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 $(i,j)\in A$.

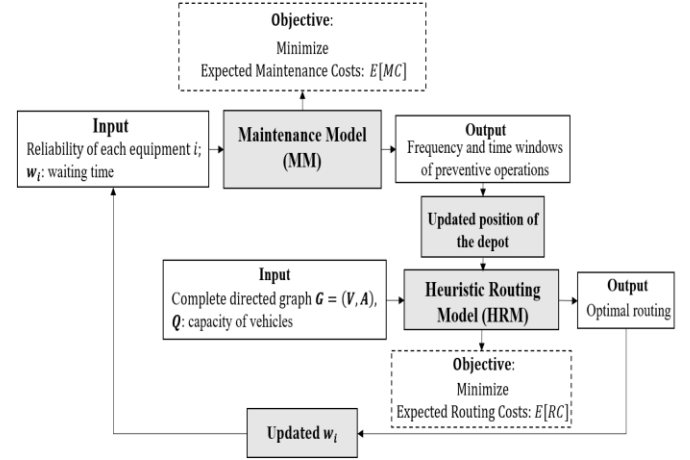


Figure 3. Principle of construction of Optimized Maintenance and Capacitated Routing Model (OMCR)

Each customer $i\in V_c$ has η_i times a PM operation over the scheduling horizon τ . The MM sub-model allows to obtain time windows for each operation $[e_j, l_j]_i$; $j=1,2,\dots, \eta_i$. We thus consider an auxiliary grouped set of nodes $V'=\{0,1,2,\dots,n\}$ where 0 is the depot and $n=\sum \eta_i$ represents the cardinal of the set of all the PM 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 $t_{i'j'}=t_{ij}$ and $d_{i'j'}=d_{ij}$. The problem therefore consists in solving a classical CVRPTW considering the graph G' such that:

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

For the rest of the paper, we use the index i instead of i' to denote each PM operation. CVRPTW is an NP-hard problem whose only small instances can be solved. The most recent and relevant model is proposed by [14]. Based on this classical model, we can define the Mixed-Integer Linear Programming model (MILP) of the HRM. However, for large instances of the problem, it is necessary to combine the MILP with a heuristic. We choose to adapt and implement a divide to conquer algorithm [15] as illustrated in Figure 4. Firstly, the large list of

¹ w_i is obtained exactly as in the CMR.

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.

PM operations is sorted from earliest to latest and divided into small sub-lists. Secondly, each sub-list is solved through the MILP and afterwards the results are combined to obtain PM operation scheduling. We can now focus on the MILP formulation. A 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 .

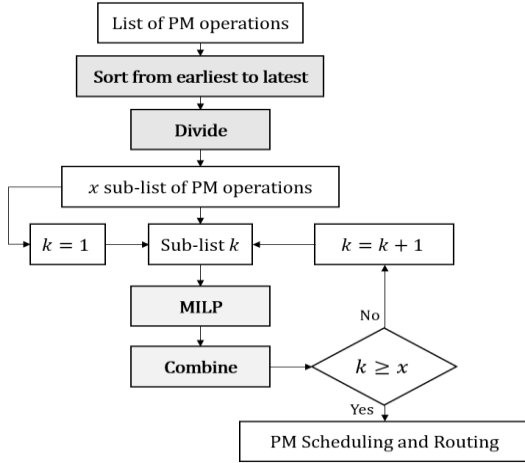


Figure 4. Divide to Conquer algorithm, adapted to the HRM sub-model

The MILP of the HRM sub-model can be stated as follows:

Minimize

$$\sum_{i=0}^n \sum_{j=0}^n (Coef.CK.d_{ij} + CH.t_{ij}).x_{ij} + Coef.CU.m \quad (1)$$

Subject to

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

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

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

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

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

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

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

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

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

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

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

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

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 PM 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 $T_{PMi} + T_{ij}$. 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 an academic case study.

IV. NUMERICAL STUDY

A. Test instances

In this section, we run the OMCR in the oil and gas field to highlight the relevance of the proposed model. We apply the general framework proposed in Section 3.1.

- (1) Equipment: we study the case of onshore pumps.
- (2) Customers: we consider ten distributed pumping stations in a radius of 300 km. 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 [11], as presented in Table 1. Secondly, we generate nine instances of the problem by randomly locating the ten pumping stations in a Cartesian plane $(0, x, y)$ (Appendix 1 for details). Then, we consider the distance between each pair of pumping stations Euclidian.

TABLE I. DATA ON PUMP'S FAILURES

i	$C_{PMi}^a(\$)$	$T_{PMi}^a(\text{hour})$	$C_{wi}^a(\$/\text{hour})$	$f_i(t)^b$
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 . [hours]

The MMW has a fleet of homogeneous vehicles whose capacity needs to be optimized. The unit costs related to each vehicle are:

$CD=0.476\$/km$, $CT=30\$/h$ and $CP=5000\$$. We consider three types of vehicles, each with a nominal speed of 80 km/h :

- (1) Medium: $Q = 4\text{ pumps}$, $Coef = 1$;
- (2) Heavy: $Q = 6\text{ pumps}$, $Coef = 1.5$;
- (3) Extra-heavy: $Q = 8\text{ pumps}$, $Coef = 2$;

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.

B. Results

The OMCR allows optimizing the PM operations of geographically dispersed equipment considering the capacity constraint of vehicles while reducing computation time. With the case study, we have conducted experiments to highlight the relevance of the proposed model. We run the iterative process until reaching 10 successive iterations where the value of $E[DMC]$ do not change to more than 1%. We run all nine instances using the general framework, first without removing the loop of depot position and second after removing it. Figure 5 presents the results obtained for the first instance with the loop.

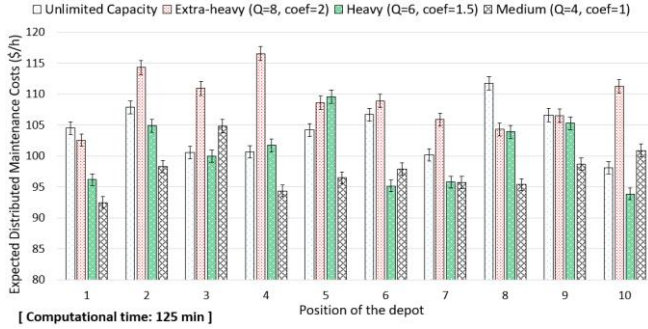


Figure 5. General framework without removing the loop of position: instance 1

It can be seen that going through the old optimization framework with the OMCR model takes 125 minutes. The best choice for vehicles is the medium size and, position 1 is the best for the depot. The optimal $E[DMC]$ is $\$92.5/h$. Then the optimal number of PM operations to perform within a month is 77, as presented in figure 6.

Table 2 and Figure 7 allow comparing the results obtained with and without the loop of depot position. First, the proposed framework allows dividing the computation time by more than ten, as presented in Table 3. And, even though it does not produce an optimal $E[DMC]$, the result remains in an acceptable interval for all nine instances. Indeed, to better interpret the results, we have defined an interval as presented in Figure 7. The lower bound is the optimal results obtained by situating the depot in the customers' locations. The upper bound is the results

obtained if the depot's position is chosen randomly and once among customers.

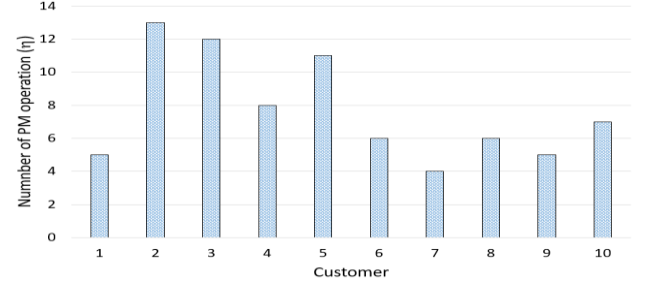


Figure 6. Number of PM operations within a month: instance 1

TABLE II. COMPARISON OF THE PROPOSED FRAMEWORK

Instances	E[DMC] (\$/h)			Computation Time (min)		
	With Loop	Without Loop	Gap	With Loop	Without Loop	Gap
1	92.5	93.1	1%	125.4	9.2	-1263%
2	87.5	90.0	3%	128.5	11.4	-1032%
3	86.1	93.6	8%	118.6	10.7	-1005%
4	93.8	99.3	6%	129.2	11.0	-1080%
5	93.7	95.2	2%	124.6	12.3	-911%
6	92.9	94.7	2%	122.3	12.2	-901%
7	89.3	92.2	3%	148.2	12.4	-1098%
8	92.3	96.3	4%	156.9	9.5	-1546%
9	88.1	95.9	8%	163.9	14.2	-1052%

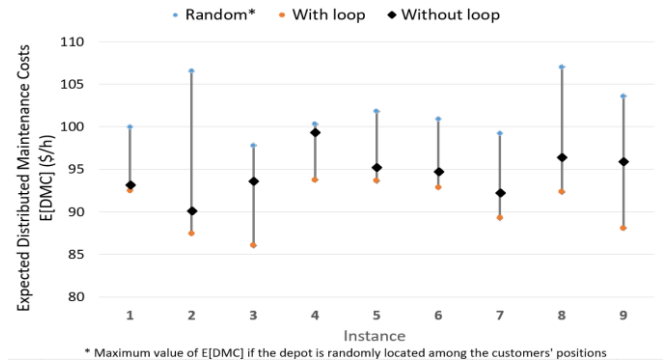


Figure 7. Interval of the results using the proposed model

Finally, by implementing the proposed framework in the nine instances, the computation time is deeply reduced, the gap between the results are less than 8%. Furthermore, in a real-world application, the number of customers is higher than ten. Managers may decide to locate the depot randomly among the clients' locations to tackle the increase in computing time. In this case, even if the computation time becomes small, the difference between the result obtained may be more than 21%, as illustrated in instance 2 of Figure 7. With the proposed framework, the results could be less.

Furthermore, Table 3 presents the selection of CMW location

and vehicles capacity for the 9 instances. It can be observed that from one instance to another, the location differs much more with the loop process than without it. The Average distance between each depot is 116km with a standard deviation of 68km with the loop rather than 43km and 29km without it. It could be interesting in the case where the company decides to add or change the position of a PS after constructing the CMW.

TABLE III. OPTIMAL PARAMETERS

Instances	Optimal position of the depot				Optimal capacity of vehicles	
	With Loop		Without Loop		With Loop	Without Loop
	x	y	x	y		
1	103	20	157	142	Medium	Medium
2	185	51	174	81	Heavy	Medium
3	93	158	164	124	Medium	Medium
4	150	51	181	158	Heavy	Medium
5	18	184	178	145	Medium	Medium
6	72	177	141	182	Heavy	Medium
7	255	169	146	195	Heavy	Heavy
8	51	130	156	165	Heavy	Medium
9	215	130	188	186	Heavy	Heavy

V. CONCLUSION

This paper deals with 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 an optimized framework and a novel model to consider the capacity constraints of the vehicles transporting spare parts and operator while reducing computation time.

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 some academic instances concerning the oil and gas industry. The study allows dividing the computation time by more than ten. And, the best costs obtained have a gap from the optimal to less than 8%

Future research based on this work could extend experiments to a more extensive case study with a higher number of customers to test the scalability of the proposed model. Furthermore, it could be interesting to 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 uncertainty of the travel time between two

production sites.

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