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Ernest Foussard[†,1,2], Marie-Laure Espinouse[1], Grégory Mounié[2], and Margaux Nattaf[1]

[1] *Univ. Grenoble Alpes, CNRS, Grenoble INP[‡], G-SCOP, 38000 Grenoble, France*

[2] *Univ. Grenoble Alpes, Inria, CNRS, Grenoble INP, LIG, 38000 Grenoble,France*

Abstract

The transition towards Circular Economy is a crucial issue of European environmental policies. It requires a complete overhaul of production systems, in order to improve product lifecycles and to reduce the ecological footprint. In this context, maintenance is key to extend the products durability. This study addresses maintenance planning optimization within the Circular Economy framework.

An original lot-sizing model for tactical maintenance planning on a single-machine with multiple components is presented. The main features of this model are the consideration of the component health index and the global budget on environmental impact. The computational limits of the model and the impact of the budget constraint are assessed through experimentations.

Keywords — Circular Economy, Lot-Sizing, Maintenance Planning, Mixed-Integer Linear Programming.

1 Introduction

Recently, the sustainability of production systems became a key concern. Indeed, there is an increasing pressure to implement environmental policies in the industry. The Circular Economy (CE) stands as one of the most promising paradigms to reform non-sustainable production systems. It consist of keeping products in a closed-loop by promoting the reusing

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†Corresponding author: `ernest.foussard@grenoble-inp.fr`

‡Institute of Engineering Univ. Grenoble Alpes

and the remanufacturing of products and/or components. The goal is to reduce resource entries and waste generation of the supply chain. CE also encourages to extend the lifetime of products by repairing them. Lately, many industrials, researchers and policy-makers have demonstrated a growing interest in CE. One of the latest examples is the new European Union action plan for CE, which aims at shifting the current production system towards a more sustainable and less resource-dependent one [3]. A key concept in CE is Performance Economy (PE), also known as Functional Economy. It consists in providing services rather than selling goods: the producer keeps ownership of his machines and sells the service. He thus remains responsible for the service level throughout the lifecycles of the machines. Laundromats or bike sharing services are examples of such business model. Preventive maintenance, i.e. any operation performed on a product with the aim to increase its durability, is central in this framework as it allows to keep the product in a satisfying service level for a longer time period.

In the field of optimization, the subject of CE is unequally covered. There are extensive studies about reverse logistics [2], sustainable manufacturing [6] and the implementation of CE in production planning [10]. However, to the best of our knowledge, the topic of maintenance planning in a CE context is yet to be studied. The purpose of this work is to address and open up new perspectives for maintenance planning optimization in the context of CE.

According to [11], preventive maintenance policies can essentially be divided into two categories: time-based maintenance and condition-based maintenance. Since end of life repurposing and recycling are key operations in CE, a special attention is paid in this work to the state of a machine component by component throughout its lifecycle. A conditional approach based on a precise measure of the component condition over time is therefore more suitable. Many studies use the virtual age of the machine or its components for that purpose: in both [5] and [8], components have a stochastic failure rate depending on their age. Breakdowns require to perform costly corrective maintenance operations and preventive maintenance operations restore the age of a component to zero. Fewer research works deal with the case of imperfect maintenance. In [11], the case of imperfect maintenance operations with percentage age reduction is investigated. In [7], on the other hand, the Equipment Health Index (EHI) is used to keep track of the condition of the machine under a time-based preventive maintenance policy. This indicator is used to determine whether a machine can safely process a job or not. The problem studied in this work contains an adaptation of the health index to machines with multiple components. A component with a low health index is more likely to break or cause overconsumption than a component in perfect state. The preventive maintenance framework proposed is very general, both perfect and imperfect maintenance, corresponding respectively to full or partial regeneration of one or several component health, are considered in the studied problem.

A more general version of the problem is investigated in [4]. The problem considers large planning horizon. Thus, different level of decision are mixed into the model (e.g. short term maintenance and long-term environmental strategy). A multi-objective mixed integer linear program (MILP) is designed. This model involves complex objectives depending on multiple parameters, and therefore computation times can be a major issue with realistic instances and low time granularity. The study of the multicriteria aspect of the problem is also challenging, as it involves four objectives functions that cannot be directly compared. This issue is overcome by separating tactical and operational decision-making into two sub problems and considering a single economic objective with a budget constraint on the environmental impact. The tactical problem consists in defining a rough mid-term maintenance policy. At the operational level, precise short-term resource allocation and maintenance schedules are defined. A model for the tactical problem is presented in this work.

This separation is inspired by tactical level and operational level production planning problems. Thus, the problem presented in this article shares many structural similarities with tactical production planning problems. As a consequence, the MILP is close to classical multi-item capacitated lot-sizing models with key differences in the way demand and setup are handled.

In this article, a modelization of the environmental aspects within a budget constraint is investigated. Such constraints have been extensively covered in recent lot-sizing studies. Four types of carbon emission constraints for lot-sizing models were first proposed in [1], namely global, periodic, cumulative and rolling constraints. These four categories were later reused as a mean of classifying such models in a literature review [10]. This idea can be extended to emissions in the broadest sense, to encapsulate any cost or output according to [9]. A similar approach is chosen for the model presented below, with a global constraint on environmental impact. The main advantage of such constraint is that it behaves as an epsilon constraint, and is therefore very suitable for a multicriteria approach. The impact of the environmental budget on the shape of the solutions is presented in this work. The main original feature in this constraint is the dependancy on the health index, to capture phenomenons such as overconsumption or increased waste emissions due to a worned component of the machine.

In Section 2, the problem and its parameters are precisely defined. In Section 3, a multi-item lot-sizing model variant is presented. In Section 4, some experimental results on generated instances are presented, computational limits are assessed and the impact of the environmental budget constraint is evaluated. Section 5 concludes this work and new research opportunities are suggested.

2 Problem statement

Let us consider a single machine with multiple components $g \in \mathcal{G} = \{1, ..., G\}$. Since we deal with tactical-level decision making, the order of magnitude of the time horizon is typically one year, sampled in time periods $t \in \mathcal{T} = \{1, ..., T\}$ of medium granularity, e.g. one week.

Due to the context of PE, based on service exchanges, a different model for demand satisfaction, taking into account the availability A_t of the machine is proposed. The demand d_t is supposed to be homogeneous over each time period, and the fraction of the demand ultimately satisfied is proportional to the availability rate of the machine.

Each component is subject to a deterministic degradation per unit of demand satisfied r_g during the exploitation of the machine, and the state of a component at the beginning of a period t is represented by its health index H_{gt}. The health index ranges from 100 (perfect condition) to 0 (unusable). The initial state of the components is denoted H_g^0.

A set of maintenance operations $m \in \mathcal{M} = \{1, \ldots, M\}$ is available and can be used to restore the health of components by reg_{gm}. Two types of maintenance operations are considered in this work: refurbishment restoring the health of one component to 100 and partial maintenance actions restoring the health of one or several components by a fraction of its total health index. Each maintenance operation has a duration p_m representing a fraction of the time period where the machine is unavailable. The economic cost can be decomposed into the cost of each scheduled maintenance operation cp_m, maintenance setup costs cf and the opportunity cost corresponding to the unmet demand, which depends on the demand d_t, the benefit from demand satisfaction pud, and the availability rate of the machine A_t. Thus, the objective function is the sum of all maintenance costs, setup costs and costs of unsatisfied demand over the time horizon.

Furthermore, the environmental impact of the planning is taken into account and bounded within a global constraint. For the purpose of this work, the environmental impact of maintenance operations are not considered, but may be taken into account in further developments. The environmental cost of the planning captures over-pollution due to the exploitation of a worn component, namely over-consumption, increased emissions... This cost is modeled as a function of the health index of the components H_{gt} and of the availability A_t.

$$c_{env} = f\left(\left(H_{gt}\right)_{g,t}, \left(A_t\right)_t \right) \leq budget$$

For the sake of simplicity, and with the aim of solving the problem by the means of mixed integer linear programming, a simple formulation based on the product of the wear level (i.e. the opposite of the health index $100 - H_{gt}$) with the availability rate is proposed.

$$c_{env} = \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} c_g \left(100 - H_{gt}\right) \cdot A_t \leq budget$$

where c_g represents an environmental penalty coefficient per component. A linearization of this constraint is proposed in section 3.

To this day, the complexity of problem remains an open question. However, due to the structural similarities with multi-item capacitated lot-sizing problems, it is expected to be NP-hard.

In order to clarify some of the key aspects of the problem statement, a small example is proposed on a single-component machine over a time horizon $T = 5$. A single maintenance operation is available, with a duration $p = 0.5$ and a regeneration $reg = 50$. The demand (d_t) is the following: $[0.5, 0.5, 1, 0.5, 0.5]$ and the degradation per unit of satisfied demand is $r = 40$. Finally, the economic costs are $cp = 1$, $cf = 10$ and $pud = 40$ and the environmental coefficient is $c = 1$. The evolution of the health index for two solution are presented in fig. 1. Maintenance occurs at $t = 3$ for Solution 1, represented by a solid line, and at time $t = 4$ for Solution 2. Both solutions are identical until $t = 3$, thus Solution 2 is represented by a dashed line from $t = 3$.

At $t = 1$, no maintenance operation are scheduled. Therefore, the machine is fully available $A_1 = 1$ and no maintenance costs or opportunity costs are charged. The value of the degradation is thus $d_1 \cdot r \cdot A_1 = 20$, and thus the new health index is 70.

The impact of the machine availability is visible in period $t = 3$: in the case of Solution 1, the maintenance operation of duration 0.5 is scheduled, therefore the machine availability A_3 is equal to 0.5. Under the hypotheses of the problem, half of the demand is not satisfied, thus the opportunity cost is then equal to $oc = pud \cdot d_3 \cdot (1 - A_3) = 20$. The total economic cost is

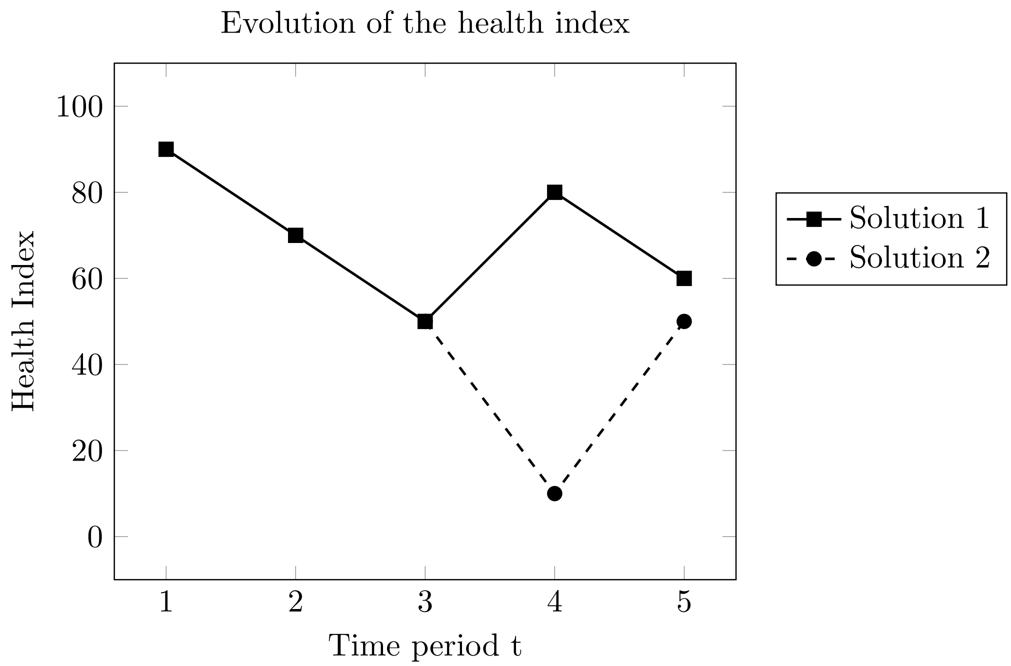

Figure 1: Two solutions of the example instance

then equal to $cf + cp + oc = 31$. The health index is also impacted by the maintenance, the variation is equal to the sum of the maintenance regeneration and of the degradation while the machine is available which results in an increase of health index by $reg - d_3 \cdot r \cdot A_3 = 30$. The availability also impacts the environmental cost, equal to $c \cdot (100 - 50) \cdot A_3 = 25$, which is higher in the case of Solution 2 since more demand is satisfied due to the absence of maintenance: 50.

The remaining part of the calculations is not detailed. Finally, Solution 1 yields an economic cost of 31 and an environmental cost of 125, while Solution 2 has an economic cost of 21 and an environmental cost of 185. These differences result from the fact that in Solution 1, the maintenance operation is scheduled early during a high demand period, while in Solution 2, the maintenance operation is scheduled late during a low demand period. With a budget of 150, Solution 1 would be feasible, but not Solution 2.

3 Model

In our framework, the health index of a component can be seen as a potential volume of demand which can be satisfied until the component is out of use. Thus, maintenance operations allow to refill the component health. This characteristic is the foundation of the comparison with lot-sizing models presented below.

The model is indexed by time, components and maintenance operations. There are four sets of decision variables: $H_{gt} \in \mathbb{R}$ represents the health index, $X_{gt} \in \mathbb{R}$ represents the regeneration value. Binary variables are: $Y_{mt} = 1$ if maintenance operation m is scheduled and 0 otherwise; $Z_t = 1$ if any maintenance operation is scheduled at time t and 0 otherwise. The availability of the machine A_t is expressed as a function of Y_{mt}: $A_t = 1 - \sum_{m=1}^{M} p_m Y_{mt}$.

The budget constraint is linearized by introducing a new set of variables B_{gmt} which represent the product $H_{gt}Y_{mt}$. Compared to classical lot-sizing models, H_{gt} is analog to the inventory level, X_{gt} to the production level, Y_{mt} and Z_t to the production setup variables.

$$\min. \sum_{t=1}^{T} cf Z_t + \sum_{m=1}^{M}\sum_{t=1}^{T}(cp_m + pud \cdot d_t \cdot p_m)Y_{mt} \tag{1}$$

$$X_{gt} + H_{gt} = H_{g,t+1} + d_t r_g(1 - \sum_{m=1}^{M} p_m Y_{mt}) \qquad \forall t \in \mathcal{T}\backslash T,\ \forall g \in \mathcal{G} \tag{2}$$

$$X_{gt} \leq \sum_{m=1}^{M} reg_{gm} Y_{mt} \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G} \tag{3}$$

$$1 - \sum_{m=1}^{M} p_m Y_{mt} \geq 0 \qquad \forall t \in \mathcal{T} \tag{4}$$

$$Y_{mt} \leq Z_t \qquad \forall t \in \mathcal{T},\ \forall m \in \mathcal{M} \tag{5}$$

$$H_{g1} = H_g^0 \qquad \forall g \in \mathcal{G} \tag{6}$$

$$H_{gt} + X_{gt} \leq 100 \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G} \tag{7}$$

$$\sum_{t=1}^{T}\sum_{g=1}^{G} c_g \left(100 - H_{gt} + \sum_{m=1}^{M} p_m(B_{gmt} - 100 \cdot Y_{mt})\right) \leq budget \tag{8}$$

$$0 \leq B_{gmt} \leq 100 \cdot Y_{mt} \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G},\ \forall m \in \mathcal{M} \tag{9}$$

$$0 \leq H_{gt} - B_{gmt} \leq 100 \cdot (1 - Y_{mt}) \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G},\ \forall m \in \mathcal{M} \tag{10}$$

$$B_{gmt} \geq 0 \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G},\ \forall m \in \mathcal{M} \tag{11}$$

$$X_{gt}, H_{gt} \geq 0, \qquad \forall t \in \mathcal{T},\ \forall g \in \mathcal{G} \tag{12}$$

$$Y_{mt}, Z_t \in \{0, 1\} \qquad \forall t \in \mathcal{T},\ \forall m \in \mathcal{M} \tag{13}$$

The objective (1) is defined by the sum of the setup costs at each period, costs of maintenance operations and the opportunity costs due to unavailability of the machine. Equation (2) represents the conservation of the components health index over time and states the relation between the health index, the wear rate and the repair volume of each component. This constraint is equivalent to the flow balance constraint in multi-item lot-sizing problems, with the notable exception of the demand term which depends on the decision variable Y_{mt}. Equation (3) and equation (5) show the relation between maintenance setup variables Y_{mt} and Z_t, and repair volume X_{gt}. These constraints are equivalent to the setup activation constraints in lot-sizing models. The health index of the components is initialized in (6). The equation (7) sets the maximum value for health index and regeneration quantity to 100.

Equation (4) ensures the non-negativity of the availability of the machine and thus limits the number of maintenance operations planned during the same period depending on their duration.

The environmental budget constraint is enforced through the remaining equations (8), (9) and (10). In this linearized formulation, it involves the product variable B_{gmt}, expressed in equations (9) and (10). Finally, the equations (11), (12) and (13) state the domain of each variable.

4 Results and Performance Evaluation

4.1 Experimental framework

The data set generation was mainly inspired by the case of laundromat washing machines, as this is frequently studied in CE and done previously in [4]. The behavior and the performances of the model are assessed on randomly generated instances of various size, according to the following protocol. The model is designed for tactical decision-making. Therefore, the horizon $T = 52$ is chosen to represent one year with a one-week granularity.

Three families of maintenance based on different characteristics are studied:

- F1 (resp F2): Single-component targeted maintenance operations. One maintenance per component is considered. The component is fully restored (resp. half restored).
- F3: Partial maintenance operations, divided into two groups of size $M = G$: operations of the first (resp. second) group regenerate 80% (resp. 20%) of the components by 20 (resp 80).

Ten instances are then generated per family with $G = 8$, and ten sub-instances are extracted from them with $G = 4$ and $G = 6$ components. These number of components are usually enough to cover the most critical parts of a laundromat washing machine. The costs and duration of maintenance operations are generated as follows. In average these values are proportional to the amount of regeneration of the maintenance. Let $S_m = \sum_{g \in \mathcal{G}} reg_{gm}$, then $cp_m \sim U\left([0.5 \cdot S_m, 1.5 \cdot S_m]\right)$. For the purpose of these tests, the bounds for the generation of p_m are computed such that one maintenance operation usually immobilizes the machine for 30% up to 60% of a period. Thus:

$p_m \sim U\left([0.004 \cdot S_m, 0.006 \cdot S_m]\right)$.

The fix cost cf is then defined as 10% of the average maintenance cost. To illustrate the variations of the demand over time, d_t is set to 0.75 during school vacations (based on the French calendar) and is set to 1 otherwise. Indeed, students can represent an important fraction of the users of PE services such as laundromats. Thus, demand might be lower during school vacations. Since the machine is not necessarily new at the beginning, H_g^0 is generated using integer uniform distributions on the respective interval $[50, 100]$. In real situations, this model might be run multiple times during the lifecycle of the machine. To illustrate the fact that some components deteriorate faster than others, the values for r_g are generated on a large interval $[2, 10]$. Finally, the value of pud is arbitrarily set to 1, as we mainly focus on parameters related to maintenance operations. This makes maintenance costs and opportunity costs equally as significant.

In a first set of experiments, the impact of the instance size is assessed. The coefficients c_g are drawn arbitrarily in the interval $[0.5, 1.5]$ such that some components have more impact than others. The environmental budget is set to 1 000 000 so the global budget constraint is virtually inactive at first.

The impact of the budget constraint is assessed in a second set of experiments restrained to the case of $F1$ with $G = 4$: the results obtained in first instance are used as baselines for comparison. The baseline environmental cost env_cost is extracted from them. New instances are then built with budgets equal to 50% and 75% of the baseline cost.

Table 1: Impact of instances size and maintenance operation types.

	G	Avg time (opt)	Avg gap (non-opt)	Avg gap	Gap min	Gap max	# opt
F1	4	64.6s	2.4%	0.4%	-	2.4%	9/10
	6	347.9s	9.2%	7.9%	-	14.5%	2/10
	8	-	15.1%	15.1%	7.7%	20.1%	0/10
F2	4	91.8s	3.7%	0.9%	-	7.1%	8/10
	6	-	5.6%	5.6%	2.3%	11.0%	0/10
	8	-	8.0%	8.0%	5.5%	12.2%	0/10
F3	4	104.7s	1.1%	0.1%	-	1.1%	9/10
	6	99.1s	2.7%	0.3%	-	2.7%	9/10
	8	60.4s	4.4%	1.3%	-	7.7%	7/10

The model has been implemented in OPL using IBM ILOG CPLEX Optimization Studio 12.10. All the experiments were done on a laptop running on Ubuntu 20.04.2 LTS, with 16 GB of RAM and one Intel Core i7-10610U CPU @ 1.80GHz $\times$ 8. The time limit is set to 10 minutes per experiment.

4.2 Impact of instances size and maintenance operation types

The purpose of the first set of experiments is to evaluate the computational limits of the approach based on the number of components and nature of the maintenance operations. The results per maintenance family are summed up in Table 1. The first and second columns show the characteristics of the instances. The third column contains the arithmetic mean of the computation time for instances which are solved to optimality in less than ten minutes. The average relative gap, computed as the ratio of the sum of the absolute gaps over the sum of the objectives for non-optimal (resp. all) solutions is provided in column four (resp. five). On the sixth and seventh columns, the minimal and maximal gaps are provided. Finally, the eighth column indicates the number of instances solved to optimality per maintenance family and number of components.

Looking at the average computation time and average gap, it appears that the nature of maintenance operations has a major impact on the performance of the model. The optimum is rarely found for the largest instances of $F1$ and the gap can be significant. For the case of 8 components, the gap is 7.7% in the best case and 20.1% in the worst case. On the other hand, it appears that in the case $F3$, most instances can be solved quite accurately or to optimality, including the largest ones.

It appears that in the case of $F1$, and $F2$ to a lesser extent, the computation time increases with the number of components and the quality of solutions decreases. In the case of $F3$, the increase is not as significant. It is likely that another unidentified parameter comes into play in this specific case.

The study of the interactions between maintenance of different families could be the object of further developments.

Table 2: Impact of the environmental budget constraints.

Budget	Avg time (opt)	Avg gap (non-opt)	Avg obj. incr.	Avg maint. incr.	# opt
50%	-	12.8%	+48.5%	+57.6%	0/10
75%	76.6s	5.2%	+7.1%	+12.0%	8/10
100%	82.8s	4.6%	+0.0%	+0.0%	9/10

4.3 Impact of the environmental budget

The second set of experiments allows to evaluate the impact of the global environmental constraint on the computation time and the nature of the solutions. The results are summarized in Table 2. The first column indicates the bound on the environmental cost. The second, third and sixth columns are the same as in Table 1. In the fourth column (resp. fifth column) the ratio of the sum of the increases of the objective values (resp. number of maintenance operations scheduled) over the sum of the objective values of the baseline instance solutions is presented.

The results presented in columns 2, 3 and 6 show that the computation time and quality of solution worsen when the budget is tighter. Most likely, the main reason for this problem results from the expression of the environmental cost as its linearization involves a large number of variables and constraints.

In this model, economic and environmental performance appear to be antagonistic. For each of the solutions obtained on these instances, the budget constraint is tight. This antagonism is clearly visible on column 4, with a 48.5% increase of the economic objective when the budget is equal to 50% of the baseline environmental cost. This increase in the economic cost is correlated with the increase of the number of maintenance operations as shown in column 5.

These results are consistent with respect to the expectations. Reducing the environmental costs requires to keep the components in a better condition. Thus more maintenance operations are scheduled and the economic cost increases.

5 Conclusion

In this article, the problem of maintenance planning in a PE context is investigated. A lot-sizing model for tactical decision-making, involving component health level and a global budget constraint on the environmental impact is proposed. Experiments on realistic sized randomly generated instances confirmed that this model can provide suitable solutions in a short amount of a time. The impact of an environmental constraint on economic profit was also illustrated on these instances. However, the model is yet to be assessed on industrial instances.

In this work the environmental impact is treated as a constraint. The integration of the environmental impact as a second objective and computation of a Pareto front could be explored and compared in future works. Finally, a natural direction for further investigation is the study of an operational counterpart of this problem, and the interaction between the solutions obtained in both situations.

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