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Abstract: Regeneration is the process restoring value to a product at the end of life, i.e. no longer used or damaged. We present a study on the evaluation of the regeneration level which aims to facilitate the regeneration industrialization. For this, it is essential to consider the health state of the product to be regenerated and to propose an evaluation method. A first part of the work proposes to identify the variables that allow to quantify the health state. A second part proposes an assessment approach based on a modeling by generalized colored stochastic Petri Net (GCSPN) and on a Monte Carlo simulation. The approach developed is tested on an industrial example from the literature to analyze the efficiency and effectiveness of the model.

Keywords: Regeneration, assessment, health state, Generalized Colored Stochastic Petri Network, Monte-Carlo

1. INTRODUCTION

Nowadays the majority of companies follow this pattern of thinking: extraction, production, consumption, and abandonment. This life cycle is linear and causes many problems such as: How to manage the increase in waste and the depletion of natural resources? According to the world population growth curve, we observe that the increase in the world's population is similar with the increase in energy, materials consumed and CO2 in the atmosphere (Arduin et al., 2019). The transition of companies to Industry 4.0 brings new technological advances with a greater source of information to solve some of these issues. Nevertheless, product customization and programmed obsolescence both generate today a significant end-of-life (EoL) product stream and for a long time (Pine et al., 1993).

The concept of circular economy based on the pillars of sustainable development is defined by the Ellen Mc Arthur Foundation as follows: A circular economy is based on the principles of designing out waste and pollution, keeping products and materials in use, and regenerating natural system (https://www.ellenmacarthurfoundation.org/circular-economy/what-is-the-circular-economy). The French Ministry of Ecological and Solidarity Transition propose a similar definition (https://www.ecologique-solidaire.gouv.fr/leconomie-circulaire).

This concept allows us to introduce regeneration, a new phase in the product life cycle. Regeneration paradigm is defined by (Diez, 2017): "set of actions, natural or technical, to restore a waste or its constituents to an acceptable state (functional and operational)".

The aim of this phase is to reduce the waste produced by man, in a circular cycle composed of a set of regeneration processes (refurbishment / recycling / reuse / remanufacturing /...). These regeneration loops enable a product to be renewed, reconstituted and extend its life cycle. Nevertheless, one question seems essential: how does one choose the optimized process of regeneration? In fact, the process that allows a product to be regenerated for the longest time and at the lowest cost will be favored among all the possibilities offered to companies.

So, this paper aims to present an approach that can help the regeneration industrialization. This work considers complete loops in the regeneration cycle as Disassembly/Reassembly (Remanufacturing) for decision-making and the assessment of different regeneration alternatives depending on the health state of a product. The health state is built for a product, as a function of functional, operational and dysfunctional variables. Indeed, when we consider EoL product, the health state depends on collected information along usage phase of product and regeneration operations. This information and the result of regeneration operations are coming with uncertainties about usage (duration of use, intensity, . . .), product's deep state (incompleteness of diagnostic test, . . .). Considering these uncertainties, a modelling method for regeneration decision support is proposed using generalized colored stochastic Petri Net (GCSPN) modelling combined with Monte Carlo simulation. We obtain a decision support tool that allows us to estimate the best regeneration trajectory.

The paper is structured as follows: a review of assessment in regeneration phase is proposed in section 2. Section 3 develops a product and process assessment for EoL product. Section 4 is dedicated to the application of the approach on an example from the literature and its analysis. Section 5 concludes the paper and sets out several ways for future researches.

2. LITERATURE REVIEW: ASSESSMENT IN REGENERATION PHASE

As we can see in the figure 1, assessment is an indispensable building block for any regeneration process. The result of regeneration will depend on the end of life product, but also on the actions of disassembly and re-assembly. The assessment must take into account all the elements that may impact regeneration result, as well as the market demand for regenerated products. Indeed, regeneration is a divergent process unlike manufacturing. So, we make the assumption to work on products with high added value that are treated individually. Thus, to help the regeneration processes industrialization, the assessment times must be as fast as possible despite the many sources of uncertainty. So, the following three paragraphs present three papers which use assessment in regeneration with heterogeneous variables.

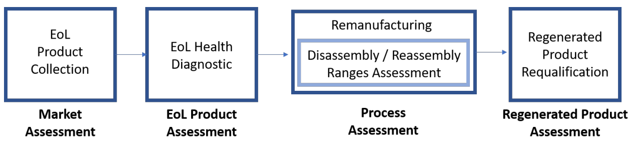

Fig. 1. Example of a regeneration cycle: Remanufacturing

For example, in the collection process, assessment is needed to estimate the potential number of EoL product which could be regenerate. For (Hanafi et al., 2008), an assessment is used to determine the optimal collection strategy in a specific location. Market variable based on demographic, historical and technological data are considered. In this work, colored PN models are developed. The first model estimates the quantity of product to be collected for a particular location. The secund allows the best alternative to be assessed simultaneously in terms of cost and environmental impact compared to the predictions of the first model. The probabilities for the estimation are fixed and based on statistical data.

Before to assess a regeneration process, EoL product health state must be assessed. In (Bentaha et al., 2020), an assessment is used to estimate the health state to find the best level of disassembly. Product variables as health state of the product and/or the states of its components/subassembly or process variables as the cost incurred to disassemble the product and the precedence constraints between tasks are considered. In this work, the uncertainty of the health state is assessed using RUP (Remaining Usage Potential) which follows a truncated normal law. Thus, thanks to the expression of constraints and a stochastic program, the researchers obtain the best disassembly sequence for a set of products (statistical optimization based on the study of a certain number of products).

For (Guo et al., 2015), a disassembly process assessment is used to find the optimal product disassembly sequence. Process variables as multiple constraints such as the availability of resources (operators, tools, machines, etc.) and precedence constraints between tasks are considered. In this work, the use of PN modeling is used to observe alternatives of combination of disassembly with the resources used. Finally, with the expression of constraints, heuristic SS algorithm solves the problem.

So, to increase profit, the best regeneration trajectory for each product should be determined in a personalized way rather than using statistical optimization of many products (Bentaha et al., 2020). Indeed, even if statistical optimization allows the importance of the assessment time to be reduced, this could lead to slowdowns in the regeneration chain because the trajectory of a few products assessed globally could disrupt the process. The articles by (Hanafi et al., 2008) and (Guo et al., 2015) do not specify calculation times - which is an important omission - given that the time criterion is crucial for the implementation of profitable industrialization for manufacturers.

It is clear from these articles that there are several assessment methods (graphical or algorithmic). In addition, each paper uses heterogeneous product, process, market and environmental variables to perform assessment. But each focus solely on one theme as disassembly or collect. In our work, we propose to consider all assessments with product, process, market and environmental variables. Thus, the assessment trajectory of an EoL product is more relevant since the variables used concern the whole of a regeneration cycle. Thanks to this global vision, it is obvious that the assessment of the regeneration trajectory will be more accurate and more profitable.

3. PRODUCT AND PROCESS ASSESSMENT FOR A EOL PRODUCT

As shown in the last section, it is only after all relevant variables for regeneration have been identified (product, process, market and environmental) that assessment will be able to determine the best regeneration trajectory for the EoL product. The first sub-section proposes a definition of the product's health state. The second, a translation into PN following the regeneration activities. Finally, the model simulation, to obtain a decision support tool that allows to determine the best regeneration trajectory according to the product's health state, process and market, is presented. With this tool, we obtain a decomposition level, success probability and potential gain.

We consider a single type of product, complete (containing all its components), which arrives in the cycle through a push flow (suppliers randomly provide EoL products). In this way, products can arrive with information about their usage, either provided by the supplier or integrated into the product (smart product), or most frequently any information requiring diagnosis and tests to assess EoL product health state. Thus, we assume that it's feasible to collect EoL product information with a certain cost.

3.1 Definition of the product's health state

The health state represents the real state of a system in the form of a vector of indicators of various kinds. Theses variables can be deterministic, uncertain and/or unknown. So, product variables are defined according to the following families: functional, dysfunctional and operational for each level of the element to be regenerated

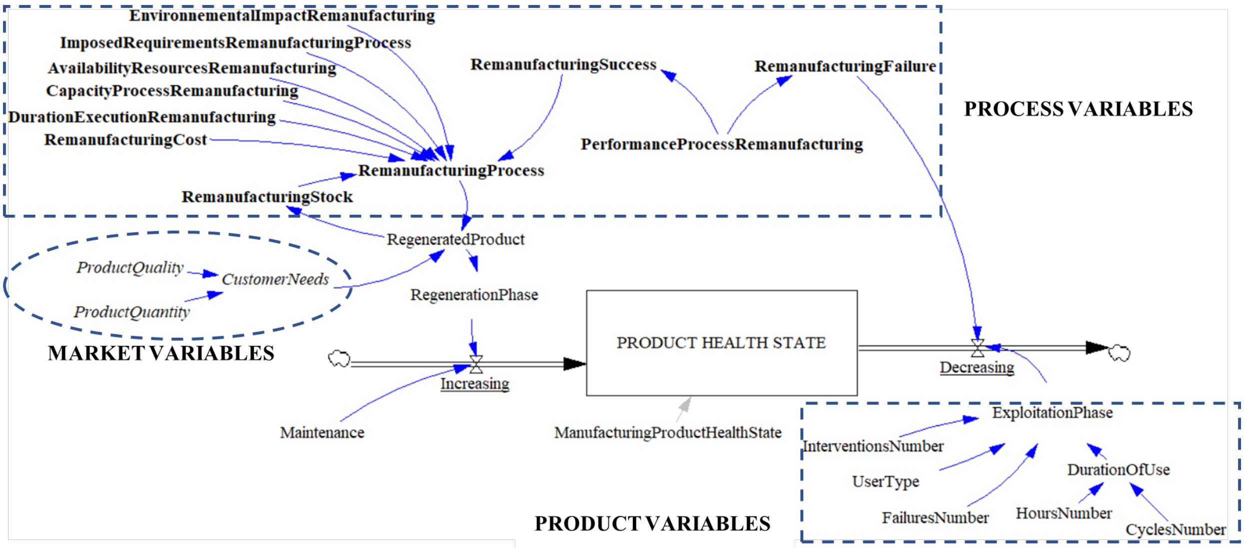

Fig. 2. Causal diagram of product, process and market variables impacting product health state

(equipment / sub-assembly / component). In the work of (Abichou et al., 2015) we find proposals for product prioritization to establish health assessment at each level. Thus, the equations established at each level facilitate the reconstruction of the health state of the higher level and the projection for the lower levels. Principles that are of particular interest to us in the cycle disassembly / reassembly.

So, the need to identify variables and their influence on the product's health state is primordial. Figure 2 presents causal loop diagram which contains a non-exhaustive list of variables impacting the product health state. The product health state variable is seen as a stock that can be filled through the "Increasing" valve and emptied through "Decreasing" (Forrester, 1994). The health state of the product evolves according to the life cycle phase it is in. The operation phase reduces the health state of the product while the regeneration phase or maintenance interventions in operation phase increase the health state. Process variables can be instantiated for each regeneration process (refurbishment, recycling, remanufacturing...) considered in the model. In addition, during its regeneration, a product can be decomposed into several elements. Thus, figure 2 is instantiated recursively for each sub-assembly and component of a product.

Figure 2 also shows that customer demands about new or regenerated product influence indirectly the targeted health state for regeneration. Indeed, regenerated product health state depending on market demand in terms of quantity and quality. If no demand, then there will be no remanufacturing.

Once all the variables are identified and we know how they influence the product's health status, then the next step is to determine the variable's nature. Some are perfectly known (deterministic), unknown or uncertain. For example, the type of user may be private information, or even unmeasurable.

The following sub-section translates the formalism presented in PN based on regeneration activities, which justifies the choice of the variables illustrated in Figure 1

3.2 Generalized colored Stochastic Petri net formalization

The first activity after collecting a product to be regenerated is to retrieve as much information about the product and data as possible from the supplier. The second activity consists in diagnosing the product's health state according to the collected information and assigning it a health class (A, B or C) which allows to categorize it. Then, the best regeneration route for the EoL product is determined according to its health state and several constraints (cost, customer needs, environmental impact, etc.). According to this assessment, the EoL product will be oriented towards the most adapted process for its regeneration (refurbishment / remanufacturing / recycling...).

One of the problems of regeneration is the decision-making activity. Indeed, the many sources of uncertainty, whether at the level of incoming products or at the level of processes, make assessment complex. The result is a lack of knowledge to define the regeneration process, increase profit and satisfy customer demands.

The objective is therefore to propose the best regeneration trajectory of a product, considering uncertainties (product and process) and constraints (ranges, cost, customer requirements...). We propose generalized colored stochastic Petri net (GCSPN) for modelling all the previous aspects (Gharbi and Ioualalen, 2007). Colored aspect allows information to be added to the tokens, which reduces the complexity and combinatorial explosion linked to the many variables considered in the model. The stochastic aspect allows the introduction of uncertainty when transitions occur (probability laws modelling uncertainty). A generalized colored stochastic Petri net (GCSPN) is defined by: $(P; T; C; Pre; Post; Inh; pri; M_0; W)$ where:

- P is a finite set of places;
- T is a finite set (disjoint from P) of timed transitions and immediate transitions;

- $C : P \cup T \to \omega$ is the color function that associates to each element $s \in P \cup T$ a color domain $C(s) \in \omega$ where ω is a set that contains finite and non-empty sets of colors. An element of $C(s)$ is called the color of s;
- Pre, Post and Inh are the incidence and inhibition functions, which associate to each place $p \in P$ and to each transition $t \in T$, an application of $C(t)$ to $Bag(C(p))$ Notes $Bag(X)$: the set of multi sets on X;
- $pri : T \to \{0; 1\}$ is the priority function which associates to each delayed transition the value 0 and to each immediate transition the value 1;
- M_0 the initial marking, is a function defined on P, such as $\forall p \in P; M_0(p) \in Bag(C(p))$;
- $W : \forall t \in T; W(t) : C(t) \to \mathbb{R}^+$ is a function which associates to each delayed (or immediate) transition, for a given color $c \in C(t)$ a crossing rate (or a weight).

The causal diagram (Figure 2) identified the variables used to define the colors and transitions of GCSPN.

In GCSPN, the places represent an element of the product nomenclature. When a token is present in a place, it means that the product is disassembled into sub-assemblies and/or components (nomenclature). The token color $C(s)$ is a tuple $(C^{Level}_{health}, C_{Level}, C^{Level}_{route})$ allows the following information to be displayed:

- Health state based on the product variables in Figure 2: C^{Level}_{health} and the resulted class from diagnosis. The color C^{Level}_{health} is defined from a variable depending on the level in the nomenclature.
- Level in nomenclature C_{Level}
- Alternatives of decomposition: C^{Level}_{route}

The evolutions of the regeneration process are represented by GCSPN. Each transition of this GCSPN corresponds to a regeneration activity:

- Health diagnosis update class variable depending on health state of the input element: $C^{Level} = f_1(C^{Level}_{health})$.
- Trajectory: determines C_{route} depending on the Product class $C^{Level}_{route} = f_2(C^{Level}_{health})$.
- Disassembly: determines the color of each sub-assembly or component obtained after decomposition. Each token has a color that depends on the health state of high level element C^{Level}_{health} , the disassembly route C^{Level}_{route} and the parameters of the disassembly process $Param_{process}$:

$$C^{Level-1}_{health} = f_3(C^{Level}_{health}, C^{Level}_{route}, Param_{process}) \quad (1)$$

- Assembly: determines the color of the assembly from the health state of n sub-assemblies or components composed high level element, the assembly route C^{Level}_{route} and the parameters of assembly process $Param_{process}$:

$$C^{Level+1}_{health} = f_4(C^{Level_1}_{health}, ..., C^{Level_n}_{health}, C^{Level}_{route}, Param_{process}) \quad (2)$$

The functions to determine the colors of an evolution take into account business strategy:

- classify product, sub-assemblies and components according to disassembly/assembly routes
- determine the disassembly/remanufacturing ranges according to stock, diagnosis, customer requests, etc.
- determine projection and reconstruction equations for product, sub-assemblies and components, according to the nomenclature.

In addition, the arrows' direction of the different variables going to either the "Increasing" or "Decreasing" valves (figure 2) allows to know when (in which phase) and how EoL product color variables change through the GCSPN transitions (improvement or deterioration). Once the model colors have been defined, regeneration activities are used to create recursive patterns to form the structure of the GCSPN. Since the variables used to define

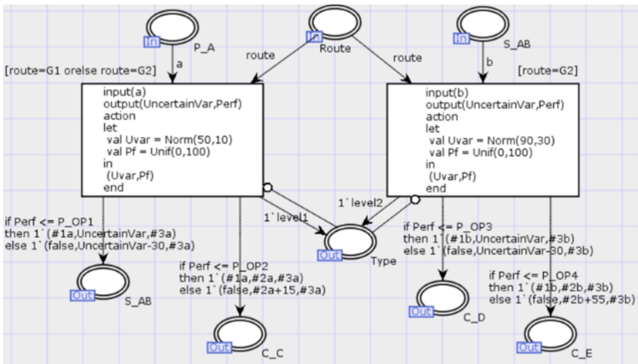

Fig. 3. GCSPN for disassembly activity

health status were not always known, some variables are formalized with an uncertainty. In order to represent this uncertainty, the value of the variable is drawn randomly following a probability law whose parameters depend on the color of the token:

- for unknown variables before disassembly, a value is drawn according to truncated probability laws (normal, uniform, ...) defined which represent the possible values variability.
- The success probability for a specific process operation, is modeled by discrete laws between 0 and 100. Depending on the draw and the result of the operation, it is either a success (the variables follow the defined equations) or a failure (the variables are degraded).

Figure 3 shows the GCSPN of the disassembly activity for a product P_A whose health status is defined by $C^{P_A}_{health} = (var_1, var_2, class_{P_A})$. Product P_A is composed of a sub-assembly S_{AB} and a component C_C. Sub-assembly S_{AB} is composed of 2 components C_D and C_E.

There are two possibilities to disassemble product P_A:

- Route G_1: If the health state of P_A is classified B, it is decomposed into S_{AB} and C_C,
- Route G_2: if product P_A is classified C, it is directly decomposed into C_C, C_D and C_E.

In the case of route 1, the following equation is used to determine the health state: $C^{S_{AB}}_{health} = (var_3, var_4, class_{S_{AB}})$. Component S_{AB} has 2 variables, var_3 is not measurable. Thus, when product A is disassembled to obtain B, the normal parameter law (m, σ) models the uncertainty of the variable. In addition, the disassembly operation is also uncertain. In 80% of cases the operation is a success. In 20% of cases, variables are deteriorated. Function transition (T_{disa}) is therefore constructed as well as the place ($P_{S_{AB}}$) represented the sub-system S_{AB} with color :

$$C_{health}^{S_{AB}} = \begin{cases} if(Perf = Unif(0,100)) \leq 80 \\ then\ (var_3 = var_1, var_4 = Norm(m,\sigma), class_{S_{AB}} = "\ ") \\ else\ (var_3 = false, var_4 = Norm(m,\sigma) - 30, \\ class_{S_{AB}} = "\ ") \end{cases} \tag{3}$$

3.3 *Simulation of the GCSPN*

From this GCSPN model, it is possible to generate different disassembly and reassembly routes. In order to evaluate them, a set of criteria such as the potential gain, the probability of reaching the desired state, the class of the remanufactured product, etc. are used. These criteria are added to the previous models in order to evaluate their value according to the health state of the incoming products and the decisions made during disassembly.

By simulating the model, many times (Monte-Carlo) with the same product variables and analyzing the results, we obtain reliable estimates that allow us to decide on the regeneration trajectory. Indeed, the model repeats the simulation as long as the stopping criteria do not converge below a chosen step. One or more criteria can be chosen to stop the simulation.

To sum up, the stochastic aspect is found at several levels in the model: random drawing of the uncertain variables of the product according to probability laws, random drawing of the process operations by discrete laws and Monte-Carlo simulation.

4. NUMERICAL ILLUSTRATION TO A REMANUFACTURING INDUSTRIAL CASE

The model is tested with an example from the literature (Bentaha et al., 2020): a Knorr-Brese EBS 1 Channel Module which allows us to verify the effectiveness and efficiency of the model. We consider 3 sub-assemblies: the cover, the cap, the support which is composed of 2 sub-assemblies (electronic card and the body). The following variables are considered for the Knorr-Brese module level. So, variables threshold are pre-defined. EBS module

Fig. 4. EBS module and components of the returned module (Bentaha, et al 2020).

$F_1 and F_2$ functionalities are tested on test benches. Module usage duration is given by the supplier and the percentage of rust is determined by observation of the module. The color of the token corresponding to the EBS module health is formed of 5 variables:

Table 1. Variables for the equipment level: Knorr-Brese

Variables	Values
Controlling brake pressures ($F_{1_{EBS}}$)	0: False 1: True
Containing the air ($F_{2_{EBS}}$)	0: False 1: True
Duration of use (D_{EBS})	0: D_{EBS} > 40k hours 1:20k < D_{EBS} ≤40k hours 2: D_{EBS} ≤ 20k hours
Percentage of rust (R_{EBS})	0: R_{EBS} > 80% 1:40% < R_{EBS} ≤ 80% hours 2: R_{EBS} ≤40% hours

$$C_{health}^{EBS} = (F_{1EBS}, F_{2EBS}, D_{EBS}, R_{EBS}, class_{EBS}) \tag{4}$$

The colors of each sub-assembly and component are defined in the same way. Some variables at module level allow, by deduction, to determine at the lower level (sub-assemblies, components) variables which represent elements that have just been disassembled (e.g. the usage support is the same for EBS duration). For variables that cannot be inferred, uncertainty must be introduced (e.g. tightness level of the valves).

For each level of nomenclature, the variables are categorized to allow classes to be defined for each element. When crossing the transition, the transition function determines the health state of the EBS module by the color:

$$C_{health}^{EBS} = \begin{cases} if(F_{1EBS} = true \wedge F_{2EBS} = true \wedge (D_{EBS} \leq 40000) \\ \wedge(R_{EBS} \leq 80)) \\ then(F_{1EBS}, F_{2EBS}, D_{EBS}, B) \\ else(F_{1EBS}, F_{2EBS}, D_{EBS}, C) \end{cases} \tag{5}$$

Next, disassembly / reassembly ranges, projection / reconstruction rules, costs, operations yield, stocks, customer demands and the laws of probability most representatives of the uncertain variables must be defined. In this application, 2 disassembly and 2 re-assembly ranges are possible. So, the route color (C_{route}) is an element of the set: $\{G_1, G_2, GR_1, GR_2, No\}$

The transition function corresponding to trajectory choice is determined using the desired state (DS) to be reached and the class of the product (C_{health}^{EBS}) :

$$C_{route}^{EBS} = \begin{cases} if(DS = A \wedge (class_{EBS} = B \vee class_{EBS} = C))\vee \\ (DS = B \wedge class_{EBS} = C) \vee (DS = class_{EBS}) \\ then(G_1) \\ else(G_2) \end{cases} \tag{6}$$

Thus, for the valve tightness level, we use a truncated normal law between 0 and 100% with as parameter a fixed standard deviation assumed to be statistically determined and an average which is a function of the equipment level service life variable (module EBS). Once the parameters of the normal distribution have been determined, a random draw in the distribution assigns a value to the tightness level.

Process uncertainty is modelled by discrete laws. Probabilities are defined according to the performance of each operation. Either the operation is a success or a failure. If it is successful, the values of the variables are affected normally according to the rules determined, otherwise the variables are deteriorated by adding or decreasing.

Before simulation, we choose the following product variables supposedly determined in the diagnostic activity upstream to the decision support model: $F_{1EBS} = true$, $F_{2EBS} = true$, $D_{EBS} = 30khours$, $R_{EBS} = 10$ which correspond to a Class B module, as well as the desired state to be reached (Class B). A stock is supposed to be null for the cover, the cap and the support but not for the electronic board and the body. The range alternatives that we are trying to assess, knowing the resale grid, are listed in the following tables: We observe the potential gain and the probability of reaching the desired state with a stopping step of 0.01 which corresponds to 1 euro-cent for the potential gain and 1% for the probability. After many simulations to reach the stopping criteria and the processing of this data, it can be decided which will be the best regeneration trajectory.

Table 2. Alternatives costs per class

Alternatives	Alternatives cost (€)
G1	1.5
G2	3.5
GR1	1
GR2	2
No	0

Table 3. Alternatives resale prices per class

Alternatives	Alternatives cost (€)
New	796
A	600
B	400
C	100

The results show that only 300 simulations are needed to stop data processing since the decision criteria no longer vary above the stop step. Thus, no time is lost and the assessment can switch to another product to be regenerated. The average potential gain is 276.66 €. The probability of reaching the desired state is 63.4%. The model uses in 52% the G1 disassembly range and in 30% no reassembly. A possible conclusion, assuming that the company's strategy is to allow regeneration of the product from a potential gain of more than 200 €, would be: disassemble the product following the G1 disassembly range.

Table 4. Summary of results

Potential gain	276.66€
Success probability	63.4%
G1 proportion	52%
No proportion	30%

5. CONCLUSION

Remanufacturing plays a key role in the valorization of Eol products. It effectively allows used products to be reintroduced directly into the market. We have proposed a definition for the product health state to be regenerated and we have proposed the use of a tool to help assess the regeneration level through generalized colored stochastic Petri nets modelling. This proposed approach takes into account some uncertainties related to the product health state and some uncertainties concerning the regeneration processes. The proposed model was applied to an industrial instance of the literature (EBS Module).

This first application showed the feasibility of the approach, but also the limits of the GCSPN modelling. The structure of the model is based on the proposed disassembly/assembly process activities, and the product information is carried by the token color. This choice of modelling implies redefining all the transition function equations if the product characteristics change. One perspective is to propose generic models regardless of the product nomenclature and the variables characterizing the health state. This generalization would allow the methodology to be applied to more complex product and processes. Our approach requires significant data collection, in order to define the EoL product's health state, so it will be necessary to rely on Industry 4.0 technologies (Zhong et al., 2017). These technologies allow the traceability of the product throughout its life cycle and to update the product's health state, during the diagnostic stage. Another perspective is to compare the statistical optimization of (Bentaha et al., 2020) and the customized assessment for each EBS module. Thus, this comparison for the same number of products would make it possible to highlight the tool which allow us to generate the most gain, regenerate more products and less waste products. In this way, we will be able to define the advantages and limits of our approach.

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