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# Coupling Prognostics and Decision Making (P&DM) Processes in PHM: A literature review and proposal of a Residual Performance Lifetime concept

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**Abstract:** Nowadays, several industries are digitizing their factories in the objective of creating smart factory as advocated by industry 4.0 paradigm. Prognostics and Health Management (PHM) concept is one of the main pillars of this transformation. Indeed, it aims at increasing industrial system reliability, availability and improving the company's competitiveness by promoting principles of failures anticipation, maintenance opportunities and proactivity. In that way, the main important processes of PHM are the Prognostics and (dynamic) Decision-Making. However, while many existing works focused on Prognostics (P) or on Decision Making (DM), very few are addressed the coupling between the P and DM (P&DM). The coupling is nevertheless fundamental when decisions have to be made with regards to very interrelated KPIs (e.g., product quality, energy performance) but also with regards to the anticipated evolution of these indicators, which will depend, at least, on the mission profile (e.g., load levels, durations) and the system degradation. So, this need of an efficient and relevant P&DM coupling for decision making is a scientific issue to be solved. In that way, this paper is defining and formalizing, through SysML diagrams, the concept of RPL (Residual Performance Lifetime) as a solution to support this P&DM coupling, mainly within the frame of Machine Tool application class. Indeed, this contribution is based on RENAULT's requirements and constraints to deploy the PHM and more specifically the P&DM on a large scale in its plants. This industrial context leads, in the paper, to instantiate and illustrate the RPL to a case of a specific machine tool called GROB.

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**Keywords:** Prognostics, Decision-Making, P&DM, Maintenance, Production, Residual Performance Lifetime.

## 1. INTRODUCTION

Industry is currently going through a transformation towards full digitalization of manufacturing processes. Internet of Things, Cloud-based Manufacturing and Smart Manufacturing are some pillars of this 4th Industrial Revolution (Industry 4.0). Digital technological advancement of production systems in the sense of Industry 4.0 made possible to optimize maintenance decisions, integrating production parameters, but it has made it more complex and difficult. The reason behind this problem lies in the considerable number of parameters monitored on a single system due to the technologies 4.0 implemented (Skima et al., 2019). For example, early degradation of production assets (at a system, sub-system and/or component level) can result to unexpected deviation in the quality of the product it delivers or unplanned downtime due to a breakdown, potentially resulting in higher production and maintenance costs. Even though this maintenance/production synergy was considered before the era of industry 4.0, it's now essential in these new production systems due to their digital complexity.

The evolution towards this synergy between maintenance and production is effectively defended by the Prognostics and Health management (PHM) community and leads to the implementation of what it's called today the predictive maintenance (Gouriveau et al., 2016). This type of maintenance is primarily built on two main processes: Prognostics and Decision-making (P&DM). The purpose of prognostics is to predict the remaining useful lifetime (RUL) at which a component/Sub-system/System will no longer perform a particular function or performances. Prognostics results are used to aid proactive decision making knowing that the goal of decision making in maintenance is to propose maintenance actions and planning. Generally, the link between

the P and DM processes (their coupling) is based on using only the results of the prognostic process (i.e. the RUL, the degradation level evolutions) in the decision-making process. In this P&DM link other elements are considered (e.g. KPI levels, mission planning) that may be related to production (Bougacha, 2020). However, this coupling is not clearly formalized at the current time.

Furthermore, this consideration of profile mission and KPIs levels is even more important for RENAULT French car manufacturer (mainly in production lines using machine tools) because its main operational strategy is willing to support the synergy between production and maintenance to take decisions in order to keep the line performance. Hence, the maintenance-production synergy must be done by considering the current system/sub-system/component degradations as well as their effects on KPIs evolution (quality, energy, and cycle time level in the future) with respect to several mission profiles. Moreover, to provide a more general decision-making tool with respect to maintenance and production actors, the considered KPI's may change. Currently no study is offering such possibilities to integrate KPIs in an explicit way (it means showing the link between the system degradation and its performance to have a clear view on each process) and consider the mission profile in the P&DM process. To enable these considerations, it is needed to analyze how they are handled in the P, DM and P&DM as a whole.

These characteristics (KPIs levels evolution and mission profile) are essential for the application domain (Renault use case) addressed by this work and that can be, in a second set, generalized to manufacturing domain. To face this challenge (KPIs levels evolution and mission profile integration), it is recommended in this paper, a P&DM coupling which is built on the concept of Residual Performance Lifetime (RPL). This concept is formalized to the

machine tool application class, and then instantiated for validation to a specific machine tool named GROB-BZ560 (at the Cléon Renault Factory, France).

To defend this contribution, the paper is organized as follows. Firstly, section 2 presents each of the two P&DM processes separately, then the existing works on their coupling. It allows to highlight scientific issues or gaps on the coupling to support mission and KPIs considerations in the synergy of production/maintenance. To solve these issues, Section 3 is proposing the Residual Performance Lifetime concept definition and formalization with an illustration on the case of GROB BZ560 Machine Tool. Finally, Section 4 proposes some conclusions and perspectives.

## 2. REVIEW ON COUPLING PROGNOSTICS AND DECISION MAKING

In the objective to identify how the elements outlined previously (KPI levels and profile mission) are integrated in the P&DM coupling issue, it is first necessary to make an overview on how the KPIs and mission profiles are integrated in the P and DM separately and then in the P&DM as a whole.

### 2.1 Prognostics (P)

Prognostics is mainly defined as the process of component degradation evolution and RULs estimation (through a degradation model) to determine the future health state of each component and the system itself. The prognostics process takes into account the current and historical health conditions, the history of maintenance actions, the past and current operating conditions and the failure modes (Lee et al., 2014), (Goebel et al., 2017). However, there are certain works on prognostics that go beyond the definitions previously given, for example, by considering the missions and the KPIs. In that way, (Tamssaouet et al., 2021) integrates the interactions between components and also the mission profile effects on a system's degradation as parameters in the inoperability input-output model (IIM). Once this task is done, the obtained model can be used in the prognostics process. In (Herr et al., 2014) they proposed that each mission has a degradation rate over the system. Similarly, (Bougacha, 2020) has proven that the future profile mission of the system affects degradation (e.g., rolling element bearing degradation is influenced by the rotating speed and the load). In their model they integrate the profile mission as a constraint.

Other works on P considered the KPIs integration in respect to the synergy Production/Maintenance. For instance, (Stetter et al., 2015) proposed a system which can provide an estimation of the energy consumption in production called PEEPS (Production Energy Estimation and Prognosis System). Based on the previous work, (Müller et al., 2017) presents a forecast method, which shall process the energy-related data combined with information about dominant parameters of the product, the usage of the machine (missions) and the environmental conditions (product-related prognostics of energy consumption). Also, (Hoang et al., 2017) proposed the prognostics of the evolution of EEI (Energy Efficiency Indicator), and the calculation of a new concept named REEL (Remaining energy-efficient lifetime) instead of the conventional RUL, to track the energy efficiency performance evolution and

then estimate the time left before the object loses its energy efficiency property.

Additionally, researchers integrated models and analysis tools for predicting quality in manufacturing systems. In (Su et al., 2006) a novel quality prognostics scheme (QPS) for plasma sputtering in TFT-LCD manufacturing processes is proposed. The QPS consists of a conjecture model and a prediction model. Furthermore, (Jain et al., 2020) proposed a low-cost digital solution to prognosticate the product quality (surface roughness, dimensions, etc.).

In conclusion, methods for estimating future manufacturing KPI values (energy consumption and product quality) have been proposed in the P, as for considering the profile mission. They are based on degradation and a model that makes the link between degradation and KPIs. Other methods forecast the KPIs directly, but it is difficult to make the link with the state of the machine because the direct KPI prognostics can depend on other factors than the machine degradation. Nevertheless, in regard to the coupling needs identified in section 1, these works do not consider the integration of these elements (KPIs levels evolution and mission profile) in an explicit way after the P to have clear vision on the process.

### 2.2 Decision-making (DM)

Decision making in predictive maintenance can be synthesized as the process that provides the future sequence of maintenance actions to manage the health of a specific system. The aim is to generate proactive recommendations about maintenance actions and plans that eliminate or mitigate the impact of the predicted failure (Bougacha, 2020), (Bousdekis et al., 2019). However, there are certain works in decision-making (named post-prognostics in some papers) that go beyond what is proposed from the previous adopted definitions, for example, by considering missions and KPIs. In that way, (De Medeiros et al., 2015) aims at integrating in the decision making the consideration of the task assignment (different mission profiles) and the maintenance recommendation, both based on PHM information in order to decide whether to maintain or not the system. Then (Herr et al., 2014) proposed to consider in the decision making the ability to choose parallel machines that are capable of performing independent and identical tasks. The objective is to determine the adequate running profile to fulfill all the missions. Other works on DM considered KPIs integration in respect to the synergy Production/Maintenance. For instance, (Darabnia and Demichela, 2013) proposed a decision-making method that allows the selection of an optimum set of maintenance procedures based on the energy savings. Instead, (Hoang et al., 2017) focused on the proposal and the integration of energy efficiency indicators within the conventional maintenance management, in particular, in condition-based maintenance decision-making.

Additionally, some works integrated product quality directly in the decision-making. In that sense, (He et al., 2017) proposed a new predictive maintenance decision making method, considering the product quality control. Also, (Ivy and Nembhard, 2005) proposed a simulation-based methodology for integrating statistical quality control in order to develop and evaluate optimal maintenance actions for a two-state system. Furthermore, (Celen and Djurdjanovic, 2015) studied a decision-making approach

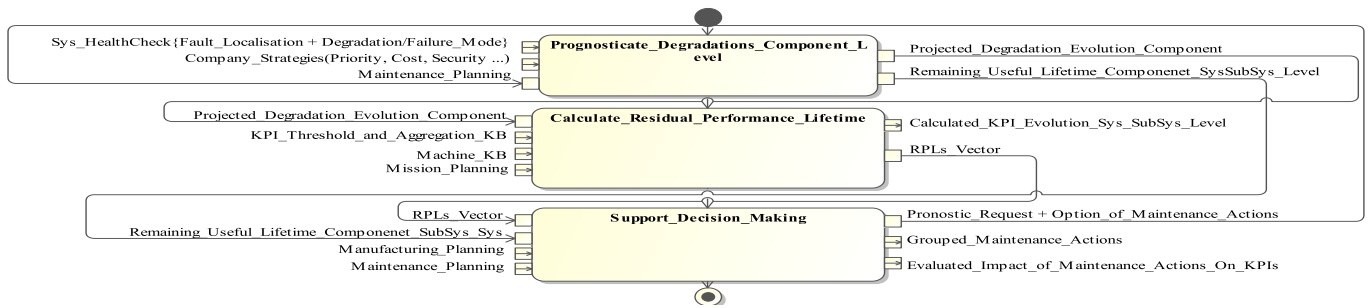


Fig. 1. RPL Process Environment – Activity diagram in black-box vision

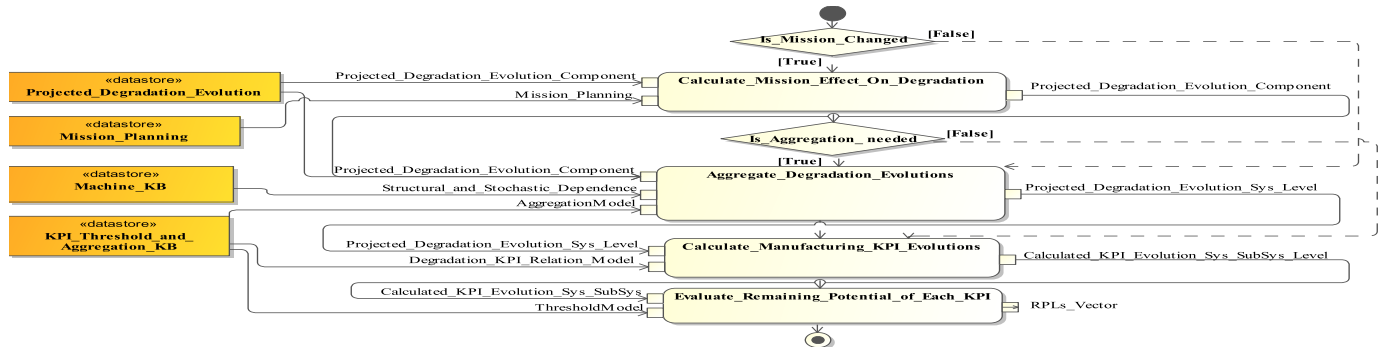


Fig. 2. RPL process decomposition – Activity diagram in white-box vision

that realizes system reconfiguration (changing of operating regimes) to counteract system degradation based on the product quality dependance with the system conditions. In conclusion, several methods providing the future sequence of maintenance actions to manage the health of a specific system were proposed considering the manufacturing KPIs values in the DM. Other methods considered the profile mission in the DM, or the energy performances, or the quality level to change the system operating regime. Few approaches have considered the mission profile as a constraint in the DM. However, in regard to the coupling needs identified in section 1, these methods do not integrate these elements (KPIs levels evolution and mission profile) before the DM to have clear vision on each process (P&DM).

### 2.3 Prognostics and Decision-making coupling (P&DM)

In this section, a study is performed to explore existing coupling approaches. In complementary way of P and DM issues, it is needed to investigate the two processes together in order to characterize their coupling as supported by formalized framework (P&DM frameworks). For example, (Combacau et al., 2000) proposed a coupling framework based on the current and future health and RUL. It is called ISHM (Integrated System Health Management). Meanwhile, OSA-CBM and ISO 13374 (Vinson et al., 2013), addressed quantitative frameworks involving prognostics and decision making. They represent some of the few existing quantitative model-based frameworks in health management.

On the other hand, (Muller et al., 2008) proposed a coupling framework based on the RUL, its level of confidence and the future performances of the system. It is called SIMP (Integrated proactive maintenance system) and use the notion of exchange flows between activities, a set of potential connections between the P and the DM (including a feedback loop from the DM to the P).

Although several frameworks propose to couple prognostics and decision making through the RUL (RUL-based coupling), the majority of these frameworks, do not integrate the consideration of the mission profile aspect and the KPI evolution aspect in the coupling of these processes in an efficient way. Nevertheless, the SIMP framework is the one that best describes the inputs and outputs of P and DM in a vision that includes explicitly the consideration of elements such as: the mission aspect corresponding to the manufacturing planning and the KPI aspect corresponding to the future performance of the system.

### 2.4 Conclusion

Although some works emphasize the coupling aspect of the P and DM processes through the calculation of the RUL, no model offers the possibility, in the P&DM coupling, to really integrate the KPI and the mission profile. Thus, we propose to formalize the link between the system degradation and its performance by integrating an intermediate process after the P and before the DM, called RPL calculation (providing to DM the evolution of KPIs levels). It leads to propose an extension to the SIMP framework to place this process between P and DM in order to solve the issue related to the integration of the mission profile and KPIs between P&DM.

## 3. PROPOSAL OF A NEW COUPLING APPROACH BETWEEN PROGNOSTICS AND DECISION-MAKING: RESIDUAL PERFORMANCE LIFETIME

The RPL concept, is proposed to be generic for the application class of machining center/machine tool (in link to Renault context). At long term, it should be extended to be generic to all manufacturing components. This contribution relies on first SysML activity diagrams, from black box functional analysis to white boxes functional analysis (a first step in the full RPL formalization). The

white-box RPL functional flow makes use of standardized data structures of SIMP coupling standards (Muller et al., 2008).

### 3.1 Definition of RPL concept

The RPL concept is defined as the residual time before the system or sub-system loses its capacity to accomplish its mission(s). By capacity, it is meaning “maintaining KPIs (product quality, energy performance and cycle time) at a certain functional level”. The difference with the RUL is that the RPL is KPI-oriented while the RUL is Degradation-oriented. The RPL can be applied at the system and sub-system level to provide a RPL vector that contains each KPI residual performance lifetime.

#### 3.1.1 Process Environment - Black Box Vision

In the black box vision **Fig.1**, the RPL concept is modeled as process facilitating the use of the prognostic output in the decision-making process (Muller et al., 2008). It is placed, within the SIMP framework used, after prognostics (without modifying P behavior) and before decision-making (without modifying DM behavior).

Indeed, the black box vision makes appear 3 main functions: **Calculate\_Residual\_Performance\_Lifetime**, with upstream: **Prognosticate\_Degradations\_Component\_Level** and downstream: **Support\_Decision\_Making**. **Prognosticate\_Degradations\_Component\_Level** calculates the projection of degradation levels at a component level and the time when the projected degradation levels are crossing a predefined threshold, corresponding to failure occurrence. This time interval is defined as RUL. It also provides **Projected\_Degradation\_Evolution\_Component** of each component. This activity takes as an input **Sys\_HealthCheck**, **Company\_Strategies** and **Maintenance\_Planning**. It provides **Remaining\_Useful\_Life\_Time\_Component** and **Projected\_Degradation\_Evolution\_Component**, this last output is required to connect the P activity with the RPL activity.

**Calculate\_Residual\_Performance\_Lifetime** calculates the time when the projected KPIs levels will cross a predefined threshold, corresponding to a loss of capacity to accomplish its mission(s). This time interval is defined as an RPL. This activity takes as inputs **Projected\_Degradation\_Evolution\_Component**, **KPI\_Threshold** and **Aggregation\_KB**: which contains information about KPIs thresholds and aggregation methods, **Machine\_KB**: which contains information about the machine decomposition and **Mission\_planning**: which contains information about the type of product that the machine produces. It provides **RPLs\_Vector** that contains the time remaining for each KPI before it exceeds a predefined threshold at the system and sub-system level. In terms of activities after the RPL calculation, **Support\_Decision\_Making** provides, based on the RPLs vector, maintenance actions and evaluate the impact of each maintenance action on the manufacturing KPIs. It provides **Grouped\_Maintenance\_Actions** and **Evaluated\_Impact\_Of\_Maintenance\_Actions\_On\_KPIs**.

In addition to the RULs and Manufacturing and Maintenance planning, **Calculate\_Residual\_Performance\_Lifetime** provides the decision-making the **RPLs\_Vector**.

#### 3.1.2 RPL Decomposition into sub-processes - White Box Vision

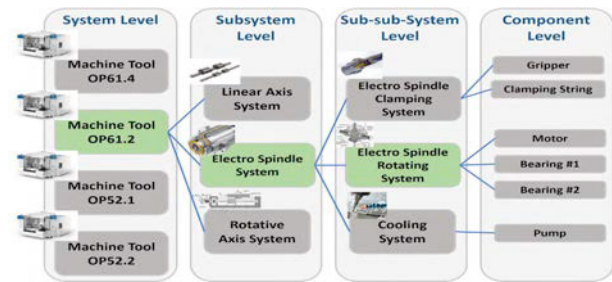


Fig. 3. Hierarchical levels for GROB BZ560 Machine-Tool

From black box vision, RPL white-box functional flow I/O is represented in **Fig.2**. The white-box activities instituting the RPL activity are described mainly with activity diagram and use the activity **Calculate\_Residual\_Performance\_Lifetime** input flows. This decomposition is based on 4 activities:

- (1) **Calculate\_Mission\_Effect\_On\_Degradation** determines the profile mission effect (**Mission\_Planning**) on the **Projected\_Degradation\_Evolution\_Component**. The future mission profile provides an operational and environmental conditions that can change or modify the degradation trajectory made by the Prognostics activity.
- (2) **Aggregate\_Degradation\_Evolutions** provides the **Projected\_Degradation\_Evolution\_Component** at a system and sub-system level. The aggregation takes by consideration the **Structural\_and\_Stochastic\_Dependence** of the system and the **AggregationModel**.
- (3) **Calculate\_Manufacturing\_KPIs\_Evolutions** calculates KPI evolutions based on **Projected\_Degradation\_Evolution\_Sys** (at system/sub-system level) and **Degradation\_KPI\_Relation\_Model**. This sub-activity provides **Calculated\_KPI\_Evolution** of the system/sub-system.
- (4) **Evaluate\_KPI\_Remaining\_Potential** calculates the time when the projected KPIs levels will cross a predefined threshold (**ThresholdModel**). This time interval is defined as RPL and is always associated to an uncertainty level. It provides a vector of the KPIs remaining performance duration constituting **RPLs\_Vector**.

After performing this first formalization of black and white vision of RPL, it is necessary now to instantiate it to a specific case, in order to illustrate the feasibility of this concept.

#### 3.2 Application of RPL concept on machine-tool use case

This application phase leads to the black and white box RPL instantiation by creating occurrences of RPL at machine-tool and sub-system levels (focus only on these two levels). For example, at the “system” level, a I/O instance of the RPLSys is defined in black box vision. Then, at the white box level, either all the sub-activities linked to the “system” level are activated or not. Furthermore, at each subsystem, an RPLSubSys is created in black box vision, its I/O are defined and then at the white box level, either all the activities linked to the “sub system” level are activated or not etc.

With regards to these levels, a machine tool (system level)

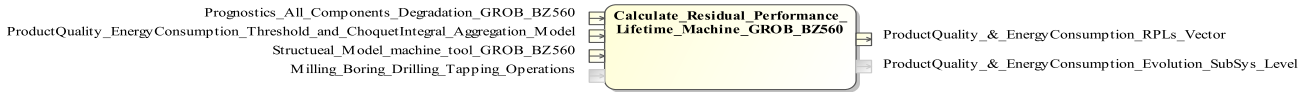


Fig. 4. RPL process black-box activity diagram – RPL instantiation GROB BZ560

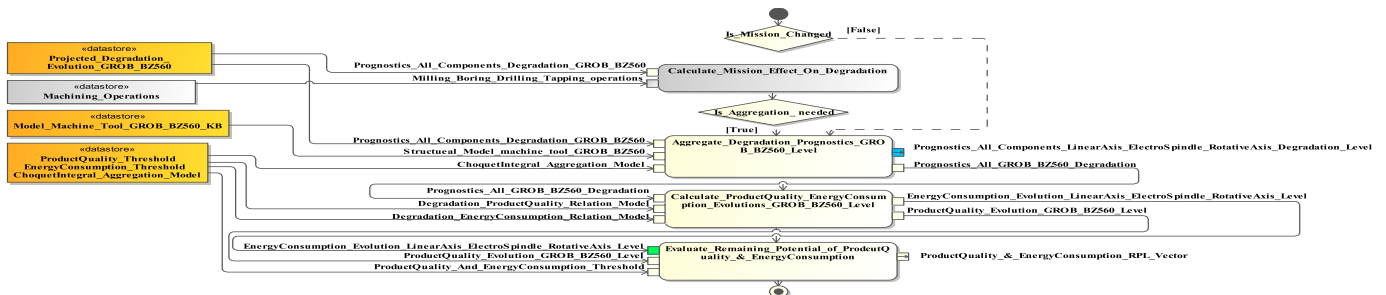


Fig. 5. RPL process white-box activity diagram – RPL instantiation GROB BZ560

is generally composed of 5 critical subsystems (Laloix et al., 2018) such as 3 linear axis, 1 electro-spindle unit, 1 rotative axe. Each sub-system is respectively composed of components (e.g., electrical motor, bearings, clamping unit). The instantiation of the proposed RPL concept is realized for the GROB BZ560 machine tool (RENAULT case) and focuses only on the Electro-spindle subsystem (critical subsystem) **Fig.3**.

This specific machine tool is able to manufacture two types of cylinder-blocks (i.e., 4626 and 4369) and uses respectively, for each type, 15 and 17 different cutting tools realizing milling, boring, drilling and tapping operations. For each profile mission there is a set of cutting tools that performs the operations on the product (cylinder-blocks). Each product is associated with a set of quality characteristics (e.g., surface location, diameter) with corresponding tolerances. Also, trajectory followed, and the cuts made that are materialized in the machine program depends on the type of cylinder-block to be machined. Finally, to confirm the impact of GROB BZ560 degradation on the product quality, the machined part measurement (cylinder-block) data are collected and an information about the degradation evolution of each component of the machine tool is also provided.

3.2.1 RPL Black & White box instantiation - GROB

In this instantiation phase, it is considered that GROB machine-tool produces only the "4626" type of cylinder-blocks. So, from the previous information provided, the black box of RPL is instantiated to GROB machine level **Fig.4**. Then, the white-box instantiation led to define the behavior and the I/O information flow exchanged between the four elementary activities instantiated to the GROB level **Fig.5**.

In the **figures 4, 5, 6 & 7** all the non-activated activities and I/O pins are colored in grey. In this example, the mission profile does not change. The link between the machine level and the electro-spindle level is done through the blue and the green I/O pins. In fact, to prognosticate the machine GROB degradation, it is mandatory to first prognosticate its sub-systems degradation mainly those of electro-spindle level.

Based on the degradation at the electro-spindle level, the **EnergyConsumption\_Evolution\_ElectroSpindle\_Level** is calculated using a **Degradation\_EnergyConsum**

**ption\_Relation\_Model**. This calculation is done similarly to the linear axis and rotative axis system to evaluate/aggregate these evolutions in order to produce an **EnergyConsumption\_RPL**. The calculation of the **ProductQuality\_Evolution\_GROB\_Level** is done at the machine level based on the degradation at the machine GROB level, using a **Degradation\_ProductQuality\_Relation\_Model**

3.2.2 RPL Black&White box instantiation-Electro-spindle

After a first step of instantiation, a second one is done at the electro-spindle subsystem level. First a black box instantiation is done **Fig.6**, then the white-box instantiation leads to define the I/O information flow exchanged between the four elementary activities **Fig.7**. The ultimate objective is to determine the energy consumption of the electro-spindle (**EnergyConsumption\_Evolution\_ElectroSpindle\_Level**). Second, after the calculation of the consumption of the different components that constitute the electro-spindle, it is aggregated to the electro-spindle level in order to calculate the electro-spindle energy consumption. It will be used at the GROB level to calculate the **EnergyConsumption\_RPL**.

As a result, the remaining duration of energy consumption is calculated both at the Electro-spindle level and the machine GROB level. Also, the impact of the Electro-spindle on product quality is calculated at the machine level. It will allow to quantify the product quality and energy consumption in order to take a decision of maintenance action to either intervene (either at machine level or at a sub-machine level) or not to maintain the nominal level of product quality and/or the energy consumption depending on the production planning.

4. CONCLUSION AND PERSPECTIVES

The integration of characteristics such as KPIs levels evolution and mission profile in the P&DM coupling is essential in the manufacturing domain in order to support the synergy between production and maintenance to take efficient decisions. Indeed, most academic studies have integrated the KPIs calculation and the mission profile in the P, others have considered these aspects in the DM, in order to couple the P and DM processes. However, no academic work has suggested to consider the integration of these elements between the P and DM to have clear vision on each process.

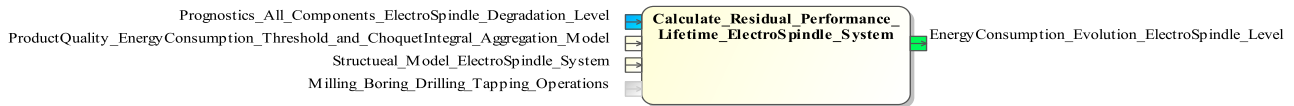


Fig. 6. RPL process black-box activity diagram - RPL instantiation Electro-spindle System

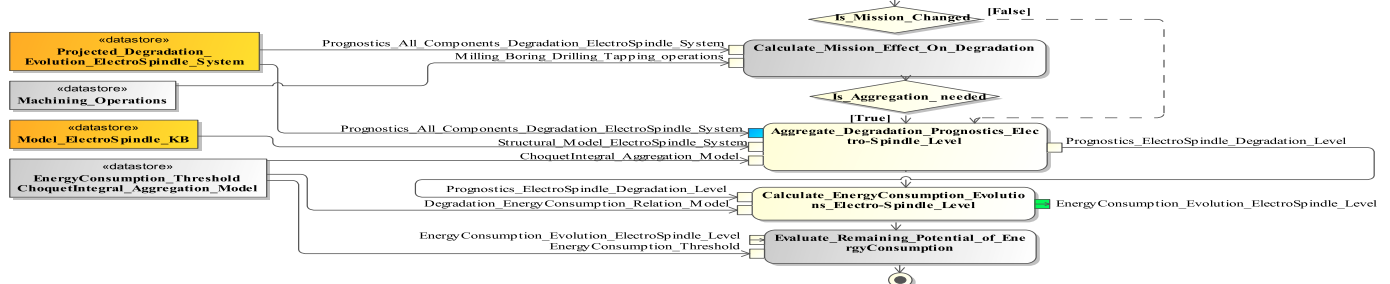


Fig. 7. RPL process white-box activity diagram – RPL instantiation Electro-spindle System

To face these gaps, an RPL concept is proposed to integrate not only the state of the asset but also the KPIs (product quality and energy consumption) and the mission profile. This P&DM is modeled through a SysML activity diagrams (from black box to white one). To highlight the feasibility and applicability of the RPL concept, an instantiation on the machine tool and then the electro-spindle sub system is realized.

In the way to fully validate these two boxes of the RPL concept, a next work is to develop a complete instantiation to the machine tool application class. In addition, the RPL concept should be confronted with other fields of applications to eventually give it a genericity of level at manufacturing layer (e.g., Robot and/or Stamping machines). Then, the formalization should be achieved by modeling behavioral and informational RPL aspects. In that way, at least algorithms must be developed for each black and white boxes activity.

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