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A prognostic function for complex systems to support production and maintenance co-operative planning based on an extension of object oriented Bayesian networks

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ABSTRACT

The high costs of complex systems lead companies to improve their efficiency. This improvement can particularly be achieved by reducing their downtimes because of failures or for maintenance purposes. This reduction is the main goal of Condition-Based Maintenance and of Prognostics and Health Management. Both those maintenance policies need to install appropriate sensors and data processes not only to assess the current health of their critical components but also their future health. These future health assessments, also called prognostics, produce the Remaining Useful Life of the components associated to imprecision quantifications. In the case of complex systems where components are numerous, the matter is to assess the health of whole systems from the prognostics of their components (the local prognostics). In this paper, we propose a generic function that assesses the future availability of complex systems from their local prognostics (the prognostics of their components) by using inferences rules. The results of this function can then be used as decision support indicators for planning productive and maintenance tasks. This function exploits a proposed extension for Object Oriented Bayesian Networks (OOBN) used to model the complex system in order to assess the probabilities of failure of components, functions and subsystems. The modeling of the complex system is required and it is presented as well as modeling transformations to tackle some OOBN limitations. Then, the computing inference rules used to define the future availability of complex systems are presented. The extension added to OOBN consists in indicating the components that should first be maintained to improve the availabilities of the functions and subsystems in order to provide a second kind of decision support indicators for maintenance. A fictitious multi-component system bringing together most of the structures encountered in complex systems is modeled and the results obtained from the application of the proposed generic function are presented as well as ways that production and maintenance planning can used the computed indicators. Then we show how the proposed generic prognostic function can be used to predict propagations of failures and their effects on the functioning of functions and subsystems.

1. Introduction

To improve their competitiveness in ever changing markets, companies need flexibility and responsiveness. This leads them to implement production equipment of goods or services ever more flexible, more responsive and therefore more complex but also more costly. With such production resources, the major challenge is to maintain them in operational condition with the highest level of availability for the lowest cost. The implementation of the Condition-Based Maintenance (CBM) and of Prognostic and Health Management (PHM) recommendations usually leads to the improvement of the equipment availability and the reduction of maintenance costs [18,20,36]. Indeed, CBM is the use of machinery run-time data to determine the machinery condition, which can be used to schedule required repair and maintenance prior to breakdown. PHM, which refers specifically to the phase involved with predicting future behavior, including the Remaining Useful Life (RUL) assessment, in terms of current operating state and with the scheduling of required maintenance actions to maintain system health, now enriches CBM [28,44]. The assessment of the RUL of components of a machinery is in fact the major issue of PHM. That is why PHM can also be implemented to guarantee the

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availability of assets, which is a typical demand in some Product-Service Systems (PSS) whose business core is to provide machine capability rather than product ownership. Indeed, PHM enables to avoid unscheduled downtimes and contract penalties in PSS [37].

In the domain of PHM, many works contribute to assess more accurately the Remaining Useful Life (RUL) before the failure, which is also called time to failure, of a critical component of a system [23,36]. This mainly consists in assessing, with a given probability, the duration of use of a component before it reaches a level of degradation beyond which the risk of failure is too high [44]. This is shown in Fig. 1 where t_0 is the current duration of use. Three main approaches are developed [15]: experience-based prognostics, model-based prognostics and data-driven prognostics [4]. The experience-based approach uses data gathered from the experience feedback to identify reliability laws. The model-based approach is based on mathematical models of the physics of degradations of components [16]. The data-driven approach consists in transforming the monitoring data provided by the sensors installed on the system into reliable behavioral models of degradations [14]. Many works aim at assessing the RULs of components or at improving the accuracy of the prognostics for many kinds of components: ball-bearings [28,43], gear trains [48,49], train pantographs [17], braking systems [10], batteries [13,19], *etc.*, but also to predict crack growth in structures [31,33].

However, only the RULs of critical components are assessed because they require sensors and data processing resources to detect failure precursors and to estimate the remaining durations of use before the degradations reach the failure thresholds which correspond to the levels of degradation beyond which the risks of failure are too high [34]. In the absence of the RUL of a component, data such as MTTF (Mean Time To Failure) or MTBF (Mean Time Between Failures) can be used [34]. In this case, the RUL is calculated by subtracting the MTTF or the MTBF from the duration of use. RULs are estimates determined from predictions and MTTFs and MTBFs are often obtained statistically. Therefore those quantities are not only scalar and they are so associated to confidence or imprecision indicators listed in [34]. That is why most of the works dealing with the prognostics of components contribute to the assessment of the RULs as well as the definitions of their Probability Density Functions (PDFs) [32].

Although these previous works dealing with prognostics are component oriented, the implementation of CBM and PHM also requires the health assessment of the whole systems as well as decision supports for maintenance planning [24,45]. Muller et al. in [29] propose the deployment of a prognosis process within an e-maintenance architecture. This integration into the e-maintenance architecture is done element by element and provides a decision support for maintenance planning from the health conditions of the components but it does not assess the overall ability of the system to perform the future tasks. Voisin et al. in [45] define a generic prognosis business process but they do not describe the process that combines the RULs and their imprecisions in order to provide the prognosis of the system although they mention its interests. A more integrated approach has been developed in [26,27]. It consists of a method to model both the system of interest and the maintenance system thanks to Probabilistic Relational Models (PRM) that are used to choose the best maintenance strategy thanks to simulations that assesses key performance indicators.

Other works also consider the production management system such as the ones presented in [1,9] that propose decision supports based on the health assessment of the systems. They requires the assessment of the risk that the systems will fail in fulfilling the operations the production planning assigns to them. This risk of failure is an input of the decision support for maintenance and production planning. Such decision supports are extended to industry to perform the maintenance activities at the better time [8]. Indeed, if knowing current and future health conditions of components is necessary to plan maintenance, knowing the ability of a system to perform future tasks is also necessary for production scheduling in order to provide a better compromise to satisfy the respective objectives of the maintenance system and of production management system [5,6,35]. Indeed, maintenance and production can plan conflicting activities on the resources they share: the machines while optimizing their own key performance indicators but may not optimize more global performance indicators [6]. Whereas maintenance determines the best practices to apply to components to set the productive technical systems at a desired availability level, production is more interested in the availability of functions of these same systems during the fulfillment of productive tasks it plans. Indeed a productive task does not necessary require the availability of all the functions of the productive system to be fulfilled. Thus productive systems can be exploited in a degraded mode (with one or maybe more unavailable functions) for some tasks while waiting for the best moment for their maintenance. This is the idea understood by “the capacity of the machine to perform the activity” mentioned in [6]. Examples are numerous: such as a five axis machine tool that can

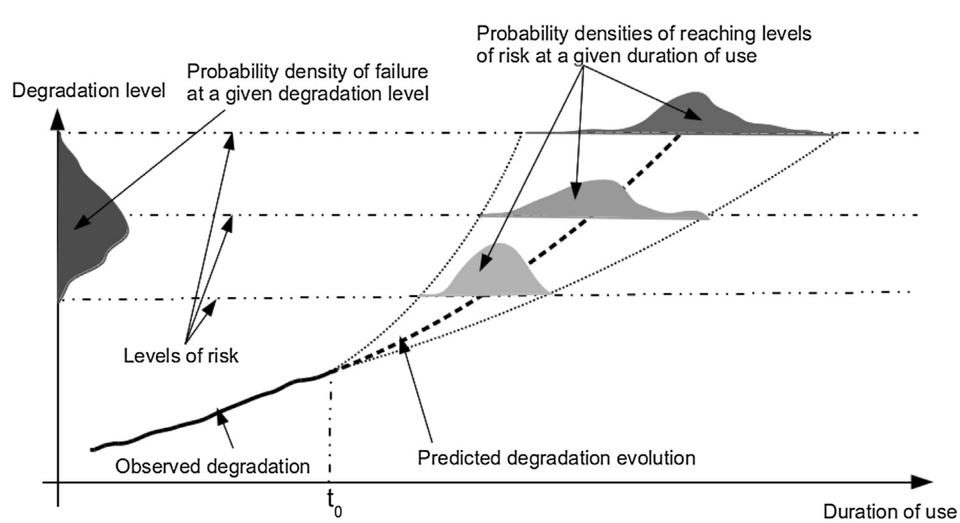

Fig. 1. Probability densities associated to RUL [44].