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Towards a generic prognostic function of technical multi-component systems taking into account the uncertainties of the predictions of their components

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Abstract— **This article presents the first elements of a generic function that assesses the capacity of technical multi-component systems to accomplish the assigned productive tasks from production planning. This assessment is based on the prognostics of their components. It must so be able to process inaccuracies and uncertainties of these prognostics. For its implementation the aimed function combines the Dempster-Shafer theory combined and Bayesian inferences. The paper presents the multi-component system modeling and the inferences for the different identified structures as well as a general algorithm. The final aim of the proposed generic function is to compute decision supports for cooperative maintenance and production management.**

***Index Terms*— Prognosis, Technical Multi-Component Systems, Uncertainty.**

I. Introduction

In order to improve their competitiveness, companies always need more flexibility and responsiveness. This leads them to invest in more complex and expensive technical systems for the production of goods or services. Therefore, one of the main challenges for companies is to keep these systems working with the highest level of dependability at the lowest cost. The implementations of Condition-Based Maintenance (CBM) and Prognostic and Health Management (PHM) concepts generally leads to improve equipment availability and to reduce maintenance costs [1, 2, 3].

The CBM consists of the data collecting process to determine the current status of machines in terms of failures during their operation for planning their required maintenance. CBM is mainly enriched by the PHM that predicts the future health of the technical systems [4, 5].

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Furthermore, many studies, as mentioned by Desforges in [6], that deal with prognosis are focused on the assessment of the Remaining Useful Lifetimes (RULs) of components (e.g., ball-bearings, gear trains, train pantographs, braking systems, batteries, etc) [7].

However the implementation of CBM and PHM also requires the assessment of the complete system health status as well as decision supports for maintenance planning [8, 9] and production scheduling that should preferably be conducted jointly [11].

The assessment of the future health of a technical system needs information related to the diagnosis and prognosis of its components. This information, particularly the one related to prognosis is inaccurate or uncertain because it is based on prediction techniques and measurements that can also fail. This evaluation therefore requires the handling of these inaccuracies and uncertainties.

To take inaccuracies and uncertainties into account, we here propose the first elements of a generic function that assesses the capacity of technical multi-component systems to carry out future tasks allocated by production planning. In the first part of this article, we will present a brief analysis of the theories dealing with inaccuracies and uncertainties of data that lead us to choose the Dempster-Shafer Theory (DST) also known as theory of evidence for the topic at hand [13]. In the second part of this paper, a modeling will be used to identify the frames of relationships between components and/or functions in multi-component systems. The third part will show the treatments resulting from DST and Bayesian inferences to assess the ability of the technical system components and functions to carry out future tasks according to the system model and the local prognostics. Finally, conclusions from these results are drawn and development prospects of this work are presented.

II. Inaccuracy and Uncertainty

Many models have chosen to ignore uncertainty to eliminate ambiguous or missing data and to consider only the known information. [10].

For example, the probability theory makes it possible to represent the inaccuracy of information, however, it does not permit us to easily represent uncertainty.

Since all measurement systems have their own features related to their accuracy, data about their accuracies must be integrated in the processes. It is also possible that these features are not well known as it is sometimes the case in domain of components prognostics as mentioned in works listed in [6]. However this could be process thanks to the implementation of the possibility theory [12]. But, when the number of component prognostic monitors becomes great, some of the monitors or their measurements may fail leading to missing data. For this reason, we have supposed that the possibility theory is not a suitable solution for the prognostic of multi-component systems from local prognostics that are prognostics of failure modes of components.

The DST offers a different point of view, it takes into account missing data for a better understanding of the situation and for making it possible to distinguish ignorance and uncertainty represented by two quantities: belief and plausibility.

The DST is a generalization of the probability theory and the possibility theory and it enables to take into account imperfect information [12, 13, 14]. Coming from only one source, data can be inaccurate and uncertain, because for costs reason, local prognostic are implemented for one failure mode for one component. The DST enables to process such data [14]. The DST is also implement for applications of data fusion, when this information is derived from data acquisition chains, analyses and models as it is the case from the prognostic of a system from its local prognostics [13].

III. Modeling of technical systems for prognosis

The implementation of a prognostic function in a technical multi-component system requires knowledge about the system: structural, functional and behavioral knowledge, but it does not require knowledge about the prognosis process itself [9].

A. Functional knowledge modeling

In systems engineering, systems are considered from different points of view. One of them is the hierarchical view. It breaks a system down into subsystems, then into functions, then into several levels of sub-functions and finally into components [15]. It is necessary to know the functions' capacities of a technical system in order to perform future tasks which are decision-making supports in the planning of future production activities.

Functional knowledge modeling aims at defining sets of entities (i.e., components or functions) which carry out the functions of a system. At the lowest level of the hierarchical structure, functions are implemented only by one or more components.

At the upper levels of the hierarchical structure, the functions can consist of components and/or functions. Finally, at the highest level, the subsystems only gather functions. Thus, the engineering process of a system allows collecting the knowledge necessary for functional modeling.

B. Structural knowledge modeling

Structural modeling aims at identifying the direct interactions between entities (components or functions) that lead to the propagations of the effects of their failures [16].

The analysis of the failure mode and their effects (FMEA), fault trees or the HAZOP studies (HAZard and OPerability) make it possible to gather the necessary knowledge for structural modeling. This knowledge can also be extracted from design models such as SADT (Structured Analysis Design Technique) or SysML (System Modeling Language) diagrams. Indeed, they allow us to identify the effects of failure of one or more components in other entities (i.e., functions or components) [17]. Therefore, this modeling represents the causal relationships between the entities of the system; however, this is considered as the functional modeling in [18].

C. Behavioral Knowledge Modeling

Behavioral modeling aims at defining the dynamic behavior of a system. They are used to detect degradation and to predict the evolution of monitored components [2]. These models are particularly used to determine the RULs of the components.

The local prognostics of components are considered to be attributes of components and constitute the function inputs of the proposed prognostic function.

A graph can be used for modeling functional and structural knowledge, where the nodes represent entities and the directed but unweighted arcs are either belonging relations (i.e., a component or a sub-function to a function) or a causal relationship (i.e., the failure of the upstream entity makes the downstream entity inoperative) [6]. In reliability diagrams [21, 22], three types of entities are considered corresponding to frames: the components, entities in serial structures that implement what we call simple functions and entities in parallel structures that implement redundancies.

IV. Assessment of the Components' Capacity and Functions to perform Future Tasks

The local prognostics of components are the inputs of the proposed prognostic function. A local prognostic is a piece of information dealing with the occurrence of one given failure of one component before the system will complete the planned productive tasks. A component can have only one failure mode. These pieces of information are supposed to be converted into basic belief assignments (bbas) for each failure. Then, the proposed prognostic function computes the bbas of the different status for all the entities of the technical system before the completion of the productive tasks. The function also indicates if the entity will become ineffective due to endogenous or exogenous causes. The computation of bbas contributes to define the technical system's capacity to perform the scheduled tasks. This is particularly the case when the bbas are evaluated for the functions of the systems because the needs of the productive tasks can be defined from the functions of the system that will be solicited.

However, the implementation of local prognostic functions for all components of a complex system would be too expensive. For this reason, data such as MTTF (Mean Time to Failure) or MTBF (Mean Time Between Failures) and their uncertainties can be used instead [19]. This information, once it has been transformed into time-dependent bbas, can be considered as local prognostics. These transformations will be the subject of further development of this work.

The first activity of the proposed prognostic function is to compute the local prognostics. This consists in evaluating the belief in terms of DST for the corresponding failure mode to occur before the completion of the planned productive tasks. The frame of discernment of a local prognostic *i* is $\Omega_i = \{F_i, \overline{F_i}\}$ where F_i is the occurrence of the failure mode *i* during the completion of the planned tasks and $\overline{F_i}$ is its non-occurrence. According to the DST, the power set of the frame of discernment must be considered. For a local prognostic *i*, $2^{\Omega_i} = \{\emptyset, \{F_i\}, \{\overline{F_i}\}, \{F_i, \overline{F_i}\}\}$ is the power set of Ω_i. For each set of 2^{Ω_i}, the bbas are provided from the local prognostic, knowing that $bba(\emptyset) = 0$. If $bba(\{F_i, \overline{F_i}\}) \neq 0$ this denotes the weight of ignorance between F_i and $\overline{F_i}$. If the X_k is one of the *n* sets of a power set 2^{Ω}, $\sum_{k=1}^{k=n} bba(X_k) = 1$. If the bbas of the members of a power set 2^{Ω} that are not singletons are nil, then the distribution of bbas is dogmatic and, in this case, the distribution of bbas on the singletons are probabilities [13].

A. Components

If maintenance policies are applied according to the CBM concept, the components are maintained before the occurrence of their failures according to their health state. With such a consideration, the failure of a component does not cause any degradation to other components because this is not supposed to happen. Taking into account this context, four states are considered for each component:

OK: the component will be able to operate within the minimum performances necessary for the planned tasks even if its performances are not the best ones due to emerging degradations.

F: The component will fail before the completion of the planned tasks. This means that the component will not be able to operate within the minimum performances necessary for the planned tasks. This state means that the failure has an endogenous origin. The component must undergo maintenance in order to be able to complete the planned tasks.

OO: The component will be out of order or inoperative before the completion of the planned tasks. This means that the component will not be able to operate within the minimum performances necessary for the planned tasks, but it will not require maintenance interventions because the origin of the failure has at least one exogenous origin. The component will be able to complete the planned tasks if one or more other components undergo maintenance.

FOO: The component will not be able to complete the planned tasks due to at least one endogenous cause and at least one exogenous cause.

The state KO is also considered. This state is the union of the states F, OO and FOO.

For a component, the frame of discernment is $\Omega = \{OK, F, OO, FOO\}$ and the bbas must be computed for all the items of 2^{Ω}, the power set of Ω. For items of 2^{Ω} which are not singletons, the bbas of those sets that are not nil, express ignorance about the states that belongs to them.

In the case of a component that has more than one local prognostic, it is necessary to combine the states of the local prognostics. The conjunctions and disjunctions proposed in the DST are mainly used to fuse data dealing with the same observation but coming from different sources. One major drawback is the explosion of the numbers of states in frames of discernments. In the present case, the sources do not observe the same thing. To avoid the explosion of the numbers of states in frames of discernments, Simon *et al.* in [19] have proposed the use Bayesian inferences in a context of reliability studies of complex systems. We here propose inferences developed from the Simon *et al.*'s proposal for the presented structures.

Before detailing the different inferences, we present a generalized inference grid and the computations based on the grid.

1) Generalized inference grid

The inference grids are used to compute, from the bbas of two frames of discernment Ω_x and Ω_y, the bbas of a third frame of discernment Ω_z. The bbas are computed for each item S_{zk} of the power set 2^{Ω_z} of a frame of discernment Ω_z excepting Ø whose bba is always nil. Knowing a given inference grid represented by the Table I, the bba of an item S_{zk} of the power set 2^{Ω_z} is computed from relation (1).

$$bba(S_{zk}) = \sum_{i=1}^{i=m} \sum_{j=1}^{j=n} \begin{cases} bba(S_{xi}).\, bba(S_{yj}), & I_{ij} = S_{zk} \\ 0, & I_{ij} \neq S_{zk} \end{cases} \quad (1)$$

TABLE I
GENERALZED INFERENCE GRID

2^{Ω_y} \ 2^{Ω_x}	S_{y1}	S_{y2}	…	S_{yn}
S_{x1}	I_{11}	I_{12}	…	I_{1n}
S_{x2}	I_{21}	I_{22}	…	I_{2n}
⋮	⋮	⋮	⋱	⋮
S_{xm}	I_{m1}	I_{m2}	…	I_{mn}

2) Plausibility and belief

Once all the bbas of an entity have been determined from the suitable inferences and the relation (1), the belief noted *bel()* and the plausibility noted *Pl()* of each item S_{xj} of power sets of the frame of discernment and of the reduced frame of discernment are computed thanks to the following relations:

$$bel(S_{xj}) = \sum_{S_{xi} \subseteq S_{xj}} bba(S_{xi}) \quad (2)$$

$$Pl(S_{xj}) = \sum_{S_{xi} \cap S_{xj} \neq \emptyset} bba(S_{xi}) \quad (3)$$

The belief and the plausibility are very interesting because they are respectively the lowest and the highest value of the probability of the item S_{xj} [23, 24].

3) Inference grids for components

The first inference grid deal with the fusion the two first local prognostics of a component. If the state of the local prognostics 1 is F_1 and if the state of the local prognostic 2 is F_2, the state obtained by the inference grid is $F_{1,2}$. If the state of the local prognostics 1 is $\overline{F_1}$ and if the state of the local prognostic 2 is $\overline{F_2}$ the state obtained by the inference grid is $OK_{1,2}$. This grid corresponds to Table II.

If the component has more than two local prognostics, the bbas of the other local prognostics will be fused with the previous ones by the means of the inference grid described in Table III.

If the component has one structural dependence with an other entities (i.e., components or functions). The KO state of the entity directly correspond corresponds to the OO state of the component. If the component has two structural dependences the inference grid presented in Table IV is used to combined them. If the component has more than two structural dependencies with other entities, the bbas of the other entity is fused with the previous ones thanks to the inference grid described in Table V.

TABLE II
INFERENCE GRID FOR COMBINING THE TWO FIRST LOCAL PROGNOSTICS

Local Prognostic 1 / Local Prognostic 2: 2^{Ω_x} \ 2^{Ω_y}	$\{\boldsymbol{F_2}\}$	$\{\overline{\boldsymbol{F_2}}\}$	$\{\boldsymbol{F_2}, \overline{\boldsymbol{F_2}}\}$
$\{\boldsymbol{F_1}\}$	$\{F_{1,2}\}$	$\{F_{1,2}\}$	$\{F_{1,2}\}$
$\{\overline{\boldsymbol{F_1}}\}$	$\{F_{1,2}\}$	$\{OK_{1,2}\}$	$\{OK_{1,2}\ , F_{1,2}\}$
$\{\boldsymbol{F_1}, \overline{\boldsymbol{F_1}}\}$	$\{F_{1,2}\}$	$\{OK_{1,2}\ , F_{1,2}\}$	$\{OK_{1,2}\ , F_{1,2}\}$

TABLE III.
INFERENCE GRID FOR FUSING THE N+1 LOCAL PROGNOSTIC TO THE COMBINATION OF THE N FIRST LOCAL PROGNOSTICS

Local Prognostics 1,2…n / Local Prognostic n+1: 2^{Ω_x} \ 2^{Ω_y}	$\{\boldsymbol{F_{n+1}}\}$	$\{\overline{\boldsymbol{F_{n+1}}}\}$	$\{\boldsymbol{F_{n+1}}, \overline{\boldsymbol{F_{n+1}}}\}$
$\{\boldsymbol{F_{1,2\ldots n}}\}$	$\{F_{1,2\ldots n+1}\}$	$\{F_{1,2\ldots n+1}\}$	$\{F_{1,2\ldots n+1}\}$
$\{\boldsymbol{OK_{1,2\ldots n}}\}$	$\{F_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}, F_{1,2\ldots n+1}\}$
$\{\boldsymbol{F_{1,2\ldots n}}, \boldsymbol{OK_{1,2\ldots n}}\}$	$\{F_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}, F_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}, F_{1,2\ldots n+1}\}$

TABLE IV
INFERENCE GRID FOR COMBINING THE IMPACT OF THE STRUCTURAL RELATIONSHIPS WITH THE TWO FIRST ENTITIES

Entity 1 / Entity 2: 2^{Ω_x} \ 2^{Ω_y}	$\{\boldsymbol{OK_2}\}$	$\{\boldsymbol{KO_2}\}$	$\{\boldsymbol{OK_2}, \boldsymbol{KO_2}\}$
$\{\boldsymbol{OK_1}\}$	$\{OK_{1,2}\}$	$\{OO_{1,2}\}$	$\{OK_{1,2}, OO_{1,2}\}$
$\{\boldsymbol{KO_1}\}$	$\{OO_{1,2}\}$	$\{OO_{1,2}\}$	$\{OO_{1,2}\}$
$\{\boldsymbol{OK_1}, \boldsymbol{KO_1}\}$	$\{OK_{1,2}\ , OO_{1,2}\}$	$\{OO_{1,2}\}$	$\{OK_{1,2}\ , OO_{1,2}\}$

TABLE V
INFERENCE GRID FOR COMBINING THE IMPACT OF ONE MORE ENTITY THE COMPONENT DEPENDS ON BY A STRUCTURAL RELATIONSHIP

Entities 1, 2…m / Entity m + 1: 2^{Ω_x} \ 2^{Ω_y}	$\{\boldsymbol{OK_{m+1}}\}$	$\{\boldsymbol{KO_{m+1}}\}$	$\{\boldsymbol{OK_{m+1}}, \boldsymbol{KO_{m+1}}\}$
$\{\boldsymbol{OK_{1,2\ldots m}}\}$	$\{OK_{1,2\ldots m+1}\}$	$\{OO_{1,2\ldots m+1}\}$	$\{OK_{1,2\ldots m+1}\ , OO_{1,2\ldots m+1}\}$
$\{\boldsymbol{OO_{1,2\ldots m}}\}$	$\{OO_{1,2\ldots m+1}\}$	$\{OO_{1,2\ldots m+1}\}$	$\{OO_{1,2\ldots m+1}\}$
$\{\boldsymbol{OK_{1,2\ldots m}}, \boldsymbol{OO_{1,2\ldots m}}\}$	$\{OK_{1,2\ldots m+1}\ , OO_{1,2\ldots m+1}\}$	$\{OO_{1,2\ldots m+1}\}$	$\{OK_{1,2\ldots m+1}\ , OO_{1,2\ldots m+1}\}$

When the local prognostics are fused between them and when the bbas of the entities from which the component depends on are fused between them too, the bbas obtained are then fused thanks to the inference grid presented in Table VI.

TABLE VI
INFERENCE GRID FOR COMBINING THE IMPACT OF ENTITIES THE COMPONENT DEPENDS ON BY STRUCTURAL RELATIONSHIPS AND ITS LOCAL PROGNOSTICS

Entities 1, 2 …m+1 / Local Prognostics 1, 2 …n+1: 2^{Ω_x} \ 2^{Ω_y}	$\{\boldsymbol{OK_{1,2\ldots n+1}}\}$	$\{\boldsymbol{F_{1,2\ldots n+1}}\}$	$\{\boldsymbol{OK_{1,2\ldots n+1}}, \boldsymbol{F_{1,2\ldots n+1}}\}$
$\{\boldsymbol{OK_{1,2\ldots m+1}}\}$	$\{OK\}$	$\{F\}$	$\{OK, F\}$
$\{\boldsymbol{OO_{1,2\ldots m+1}}\}$	$\{OO\}$	$\{FOO\}$	$\{OO, FOO\}$
$\{\boldsymbol{OK_{1,2\ldots m+1}}, \boldsymbol{KO_{1,2\ldots m+1}}\}$	$\{OK, OO\}$	$\{F, FOO\}$	$\{OK, F, OO, FOO\}$

Thanks to the grid of Table VI, the bbas of all the items of the power 2^{Ω} of the frame of discernment $\Omega = \{OK, F, OO, FOO\}$ of a component are obtained. These bbas define the ability of the component to complete the planned tasks. A reduction of the frame of discernment by the union of the states F, OO and FOO into the state KO is done to process the bbas of entities depending on it. Using the inference grid of Table VI, this corresponds to replace F, OO and FOO by KO without duplicating the KO label.

B. Serial Structures

Serial structures are carried out by entities (components and sub-functions). The serial structures become inoperative before the completion of the planned tasks if at least one of their entities, by which they are implemented, becomes inoperative. Functions, implemented by several entities that all must be operational to be performed, are also serial structures. Considering that a component belonging to a serial structure is maintained before its failure, it will not cause any degradation to other entities, because it is not supposed to happen thanks to condition based maintenance enabled by the aimed prognostic function. Thus, two states can be considered for each serial structure, these states are:

OK: The serial structure will be able to operate within the minimum performances necessary for the planned tasks.

KO: The serial structure will become inoperative; this means that it will become unable to operate within the minimum performances necessary for the planned tasks because of the failure of, at least, one of its entities or because at least one of its entities, at least, is out of order.

For a serial structure, the frame of discernment is $\Omega = \{OK, KO\}$ and bbas must be computed for all the items of 2^{Ω} the power set of Ω. For the items of 2^{Ω} which are not singletons, the bbas of those items that are not nil, express ignorance about the states that belongs to them.

The inferences are defined from the grid presented in Table VII. These inferences process the case of a serial structure made of two entities. If the serial structure is made of more than two entities, the inference grid presented in Table VIII is then used to fuse the bbas of the additional entity with the ones that have already been obtained.

TABLE VII

INFERENCE GRID FOR COMBINING THE IMPACT OF THE TWO FIRST ENTITIES BELONGING TO A SERIAL STRUCTURE

Entity 1 \ Entity 2 (2^{Ω_x} \ 2^{Ω_y})	$\{\boldsymbol{OK_2}\}$	$\{\boldsymbol{KO_2}\}$	$\{\boldsymbol{OK_2},\boldsymbol{KO_2}\}$
$\{\boldsymbol{OK_1}\}$	$\{OK_{1,2}\}$	$\{KO_{1,2}\}$	$\{OK_{1,2},KO_{1,2}\}$
$\{\boldsymbol{KO_1}\}$	$\{KO_{1,2}\}$	$\{KO_{1,2}\}$	$\{KO_{1,2}\}$
$\{\boldsymbol{OK_1},\boldsymbol{KO_1}\}$	$\{OK_{1,2},KO_{1,2}\}$	$\{KO_{1,2}\}$	$\{OK_{1,2},KO_{1,2}\}$

TABLE VIII

INFERENCE GRID FOR COMBINING THE IMPACT OF ANOTHER ENTITY BELONGING TO A SERIAL STRUCTURE

Entity 1, 2…n \ Entity n + 1 (2^{Ω_x} \ 2^{Ω_y})	$\boldsymbol{OK_{n+1}}$	$\boldsymbol{KO_{n+1}}$	$\{\boldsymbol{OK_{n+1}},\boldsymbol{KO_{n+1}}\}$
$\boldsymbol{OK_{1,2\ldots n}}$	$\{OK_{1,2\ldots n+1}\}$	$\{KO_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$
$\boldsymbol{KO_{1;2\ldots n}}$	$\{KO_{1,2\ldots n+1}\}$	$\{KO_{1,2\ldots n+1}\}$	$\{KO_{1,2\ldots n+1}\}$
$\{\boldsymbol{OK_{1,2\ldots n}},\boldsymbol{OO_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$	$\{KO_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$

Once the bbas of all the entities are fused, the bbas for the serial structure are obtained. These bbas define the ability of the serial structure to complete the planned tasks.

C. *Parallel structures*

A parallel structure ensures its service until all its entities are the in failed state or become out of order. Such structures corresponds to redundant entities (functions or components) that implement a same service, more often, for reliability purpose. If there is only one entity that is able to perform the service, there is no more redundancy and, in many cases, the system must not begin a new task mainly because of safety reasons [20].Therefore three states can be considered for each parallel structure:

OK: The parallel structure will be able to operate within the minimum performances necessary for the planned tasks thanks to one of its entities at least.

KO: The parallel structure will become inoperative. This state means that it will become unable to operate within the minimum performances necessary for the planned tasks because none of its entities will be able to ensure the service to complete the planned tasks.

LR: Redundancy will be lost. This means that only one entity that implements the parallel structure will be able to provide the service for which it was designed for. This state is very important because if the belief and/or the plausibility of this state is too high, the system must not be requested to do the planned productive tasks for safety reasons and components must undergo maintenance.

For the parallel structure, the frame of discernment is $\Omega = \{OK, LR, KO\}$ and the bbas must be computed for all the items of 2^{Ω} the power set of Ω. For items of 2^{Ω} which are not singletons, the bbas of those items that are not nil, express ignorance about the states that belongs to them.

The inferences are defined from the grid presented in Table IX. In this grid the inferences process the case of a parallel structure made of two entities.

TABLE IX

INFERENCE GRID FOR COMBINING THE IMPACT OF THE TWO FIRST ENTITIES BELONGING TO A PARALLEL STRUCTURE

Entity 1 \ Entity 2 (2^{Ω_x} \ 2^{Ω_y})	$\{\boldsymbol{OK_2}\}$	$\{\boldsymbol{KO_2}\}$	$\{\boldsymbol{OK_2},\boldsymbol{KO_2}\}$
$\{\boldsymbol{OK_1}\}$	$\{OK_{1,2}\}$	$\{LR_{1,2}\}$	$\{OK_{1,2},LR_{1,2}\}$
$\{\boldsymbol{KO_1}\}$	$\{LR_{1,2}\}$	$\{KO_{1,2}\}$	$\{LR_{1,2},KO_{1,2}\}$
$\{\boldsymbol{OK_1},\boldsymbol{KO_1}\}$	$\{OK_{1,2},LR_{1,2}\}$	$\{LR_{1,2},KO_{1,2}\}$	$\{OK_{1,2},LR_{1,2},KO_{1,2}\}$

If the parallel structure is made of more than two entities, the inference grid presented in Table X is then used to fuse the bbas of the additional entity with the ones that have already been obtained.

TABLE X

INFERENCE GRID FOR COMBINING THE IMPACT OF ANOTHER ENTITY BELONGING TO A PARALLEL STRUCTURE

Entity 1, 2…n \ Entity n + 1 (2^{Ω_x} \ 2^{Ω_y})	$\{\boldsymbol{OK_{n+1}}\}$	$\{\boldsymbol{KO_{n+1}}\}$	$\{\boldsymbol{OK_{n+1}},\boldsymbol{KO_{n+1}}\}$
$\{\boldsymbol{OK_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1}\}$
$\{\boldsymbol{LR_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1}\}$	$\{LR_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$
$\{\boldsymbol{KO_{1;2\ldots n}}\}$	$\{LR_{1,2\ldots n+1}\}$	$\{KO_{1,2\ldots n+1}\}$	$\{LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$
$\{\boldsymbol{OK_{1,2\ldots n}},\boldsymbol{LR_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$
$\{\boldsymbol{OK_{1,2\ldots n}},\boldsymbol{KO_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$
$\{\boldsymbol{LR_{1,2\ldots n}},\boldsymbol{KO_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$	$\{LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$
$\{\boldsymbol{OK_{1,2\ldots n}},\boldsymbol{LR_{1,2\ldots n}},\boldsymbol{KO_{1,2\ldots n}}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$	$\{OK_{1,2\ldots n+1},LR_{1,2\ldots n+1},KO_{1,2\ldots n+1}\}$

Once the bbas of all the entities have been fused. The obtained bbas define the ability of the parallel structure to complete the planned tasks. A reduction of the frame of discernment by the union of the states OK and LR into the state OK is done to process the bbas of entities depending on it. Using the inference grid of Table X, this corresponds to replace LR by OK without duplicating the OK label.

V. ALGORITHM OF THE GENERIC FUNCTION

The proposed generic function consists of a graph traversal in which the bbas are calculated for every vertex (a component, a parallel structure or a serial structure) from bbas of the reduced frame of discernment of its predecessors, from its local prognostics if the vertex is a component and from the proper inference grids. This function consists of five main stages:

1. The modeling graph of the technical system is instantiated.
2. The bbas for each local prognostic of every component, which are in the different states of each of the nodes, are set to zero.
3. The bbas for each local prognostic of every component is determined by the proper methods for the instant *t* at which the planned productive tasks will be achieved.
4. For each component, the bbas are calculated according to the inference grids mentioned in section IV and relation (1).
    a. If at least one bba is modified, then the bbas of of its successors (components and structures) are calculated.
    b. Then, recursively to stage 4.a.
5. Finally, the results of the proposed generic function are displayed and/or stored. They consist of the set of vertices for which we get their bbas, and their plausibility and belief values computed from relations (2) and (3) for all the items of the power sets of their frames of discernment.

VI. CONCLUSIONS AND PERSPECTIVES

In this paper, the first elements a generic function for the prognostics of complex systems were presented. It is based on the local prognostics about the failure modes of their components. This function takes into account uncertainties about the local prognostics. Thus, it implements the DST and Bayesian inferences to avoid the explosion of the numbers states in the frames of discernment. The function provide, for all its entities (components, functions, serial and parallel structures), bbas belief, and plausibility for each item of their power sets of their frames of discernment that can then be handle to become decision supports for maintenance planning and production scheduling.

However, the bbas and belief and plausibility are not obvious to handle for human beings that shall make decision from them. Further works will explore the ability of pignistic transformations to ease the decision making process for maintenance and production planning. Another development should be made in order to identify the components that should undergo maintenance as it is proposed in [6] where this is done in an implementation based on object-oriented Bayesian networks.

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