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New Approach to Prognostic System Failures ⋆

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Abstract: To obtain high availability with reduced life cycle total ownership costs, classical maintenance policies are not sufficient. Indeed these polices do not allow us to thrust in just when its necessary because they are not available to plan the current system state in the future. The paper presents an approach based on the system decomposition in three levels: Environment, Mission and Resources, to predict the system failure by tracking its various degradation and thus to know whether the system is able to accomplish its mission in time by using system current state and its future use.

1. INTRODUCTION

Classical maintenance policies consist of corrective maintenance (CM) and preventive maintenance (PM). In CM policy, systems are maintained after the failure has occurred. CM causes unexpected system stops and thus a loss of money and time. In PM, system equipments are replaced according to schedule based on equipments time life. PM is expensive because of frequent replacement of costly equipments. Moreover studies show that the number of equipments operating hours is not the only factor which impact on the failure occurrence Thus, PM increases system availability compared to CM but is not cost-effective. Therefore these maintenance policies are not sufficient to obtain high availability with reduced life cycle total ownership costs.

To improve PM, the Condition Based Maintenance (CBM) uses real-time information to optimize the maintenance of equipments, and to repair only when maintenance is actually necessary. CBM consists of equipments health monitoring to determine the equipment state. However CBM is not able to predict the equipment future state based on the current equipment state and its future operating conditions. A prognostic capability is thus necessary to know if the system is able to accomplish its mission and to avoid failure occurrence in operating condition. This maintenance policy is called predictive and proactive maintenance.

In this paper, an approach based on the Mission, Environment, and Resources (MER) for systems modelling in order to prognostic failures is presented. This paper is organized as follows: in section 2 the problematic of the prognosis is discussed. In section 3 a review of prognostic approaches is given. The proposed MER approach is detailed in section 4. Finally, conclusion and future works are given.

⋆ This work on the prognosis of warship is realised in LSIS laboratory and carried out in collaboration with DCNS and PREDICT.

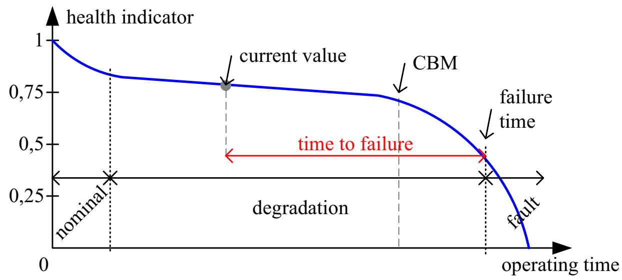

Fig. 1. Simple health indicator trajectory, time to failure is a function of the operating time

2. PROGNOSTICS PROBLEMATIC

Currently, there exist prognostic methods for equipments which are some health indicators. These indicators are based on statistics gathered over a large equipment population (Brotherton et al. [2000]). Consequently although these indicators are an average, they do not account for the equipment which is monitored . These indicators are essentially based on operating time. Figure 1 shows an example of a health indicator. The health trajectory and maintenance thresholds (nominal, replace, fault) are function of the operating time. The equipment is following a known fault-life degradation path. In this case the time to failure can be predicted by estimating the health indicator value.

To be more realistic, the health trajectory is not only a function of time but depends also on the equipment use and the environment where it evolves. As shown on figure 2, the health indicator trajectory switches between various curves. Each curve is plotted for specific constraints (equipment use and environment) and characterizes operating modes. In this case maintenance threshold are defined in function of equipment health.

To realize a prognostic, first, the current health indicator value and operating mode must be estimated and then the health

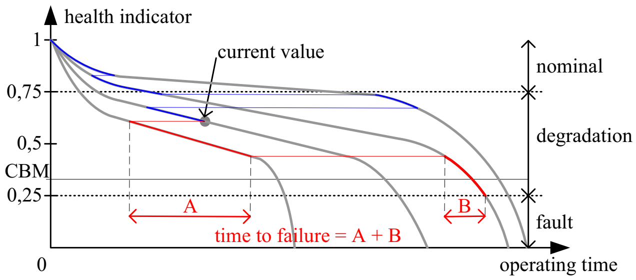

Fig. 2. More real health indicator trajectory, time to failure is a function of the operating time

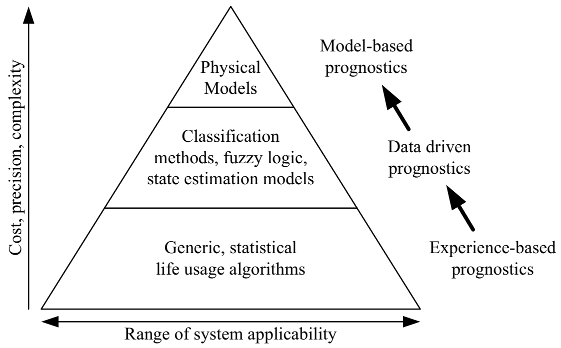

Fig. 3. More real health indicator trajectory, time to failure is a function of the operating time

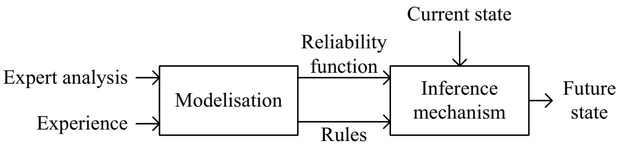

Fig. 4. Structure of experience based prognostics approaches

indicator should be projected in the future. The projection is possible if the operating mode sequence or one or more probable sequences are known.

3. REVIEW OF PROGNOSTIC APPROACHES

The prognosis approaches are classified into three classes in function of their applicability and relative costs (Byington et al. [2003], Lebol et al. [2001]). The hierarchy of these classes is illustrated on figure 3.

3.1 Experience based prognostics

This kind of prognostic is the least complex and requires the equipment failure history data. Thus experience based prognostic is applicable to mass production equipment. This class is based on probabilistic modeling of the degradation. Usually failure and expertise data are compiled from legacy systems and experts. A statistical distribution is fitted to the data. Rules defined by human maintenance experts can be used to represent heuristics. An expert system provides the inference mechanism to perform the future equipment state from the current state as shown on figure 4.

When the physical model of the equipment is difficult to obtain, and it is impossible to monitor the degradation state with the sensor network, the experience based prognostic may be the only alternative (Byington et al. [2002]). These approaches can be used for a maintenance interval (Fig. 1).

3.2 Data driven prognostics

Data driven prognostic is based on the use of symptoms or degradation indicators. The future progression of these indicators is performed using a statistical method. Approaches of this class are gathered according to statistical and learning methods (Byington et al. [2002], Roemer et al. [2005]).

Evolutionary/Feature based prognostic: These prognostic methods track and trend deviations of specific features or measurements from their normal operating conditions. The choice of the statistical method depends on the number of features and the number of operating modes. Simple methods can be used such as linear regression, exponential smoothing, partial least square or more complex ones such as principle components analysis, canonical variant analysis, etc. (Luo et al. [2003]).

Machine learning/Artificial Intelligence Trend analysis prognostic: The main method used is artificial neural network (Zemouri et al. [2002]). The network is trained using measured or extracted features during the occurrence of failures. Once the network is trained, it is used to predict or detect the same features progressions for different tests under similar operating conditions. The network inputs are features from t_{k-n} to t_k and the network outputs are either features at t_{k+T} or the current state of the equipment. In the first case the network realizes an extrapolation of the features (Zemouri et al. [2002]) and in the second case a classification of the features.

State estimator prognostic: Kalman filters or other tracking filters can also be used as a prognostic technique. They are tools for the estimation of unknown states by combining current measurements and recent state estimation (Yang et al. [2002]).

Data driven approaches efficiency is highly dependent on the quantity and the quality of the system operational data. These approaches require that the number of sensors is high enough to follow the degradation. The key of data driven prognostic is to find measurements or features that are relatively unchanged unless a malfunctioning event occurs in the system.

3.3 Model based prognostic

The models used in this class, are physical based models, and and mathematical models.

In the first case, model based residuals can be used as features. Residuals correspond to the difference between the real measurements issued from the sensors and the outputs of a mathematical model. This assumes that the residuals are large in the presence of malfunctions and small in normal disturbances (noise and modelling errors).

In the second case, degradation models (damage accumulation) are used (Fig. 5). These models could be a structural dynamic system as first or second order nonlinear equations (Adams [2002]) considered like a slow time process and coupled with the system model (Luo et al. [2003], Chelidze [2002]). To obtain the time to failure from the estimation of the current degradation state, the coupled model is initialized with this estimation and simulated until the failure threshold. The coupled model simulation is complex because the fast time model

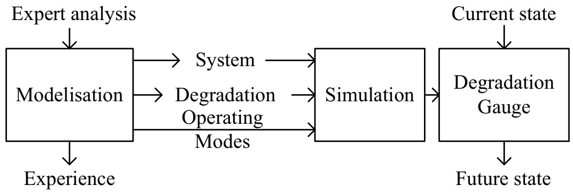

Fig. 5. Structure of model based prognostics approaches

depends on the slow time model evolution and the slow time model evolution depends on the real system (fast time model) solicitation. Various operating modes could be considered to improve the accuracy of prognostic (Luo et al. [2003]).

3.4 Combination of Approaches

Müller [2005] proposed a prognostic process based on the three approach classes mentioned previously. This process goal is to perform an estimation of system performances at time $t + \Delta t$ from the observation of the system current state at time t and a provisional list of the maintenance actions during $[t,\ t + \Delta t]$. This approach combines a probabilistic approach for degradation mechanism modelling and an event one for dynamical monitoring . First the system is modelled through a functional analysis. The system is decomposed into several subsystems and subsystems are also decomposed until the equipment level is reached. Then, the obtained model provides information to build the structure of a probabilistic model which is completed by the failure mode and effects analysis, the hazard and operability study, the knowledge of the physical relationship between subsystem and database and/or expert's knowledge to define the probabilistic model parameters. This model is implemented by a dynamical Bayesian network. It represents the causal relationships and temporal degradations. The event model formalizes the current state of the system issued from the supervision and the maintenance actions applied to the equipments. The prognostic model is the coupling of the probabilistic and event model. The prognostic is performed by initializing the prognostic model with the current system state and the maintenance actions plan (definition of the simulation scenario), then by an iterative inference of the dynamical Bayesian network.

3.5 Approaches conclusion

Experience, Data driven and model based prognostic approaches are equipment oriented. They are not directly applicable with complex dynamical systems. The approaches combination (Müller [2005]) allows realizing a prognostic on a complete system. In all presented approaches the notion of operating mode is not really explicit, but the degradation propagates according to the system use and the environment where the system operates. Thus to perform a best prognostic, it is necessary to have a prognostic model which includes "where" and "how" the system is used.

4. THE MER APPROACH

The ship is a complex system whose total modelling with only one kind of model is difficult and even impossible and definitely useless because all subsystems/equipments are not solicited simultaneously. Indeed the use of these subsystems depends on the ship activity and the environment where they work. To have a more realistic model, it is proposed to describe a complex system like a ship according to three levels as shown on figure 6. The "mission" level defines the ship use (activity) during a given period of time. The "resources" level corresponds to the means which allow achieving a pre-defined mission. The "environment" level is the conditions wherein the mission is executed and the resources used. On figure 6, influence relationships between each level are also reproduced.

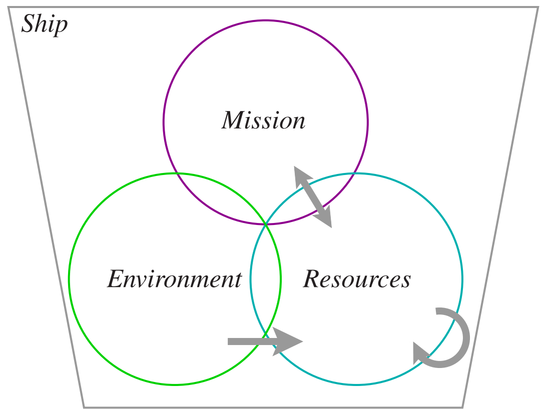

Fig. 6. The three levels of the MER approach

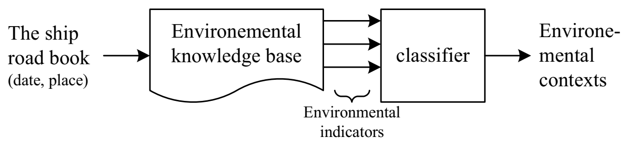

Fig. 7. The environmental level of the MER approach

4.1 The Environement

The environment is all that can influence the behavior of the resources, and thus modify their degradation rates. The environment is described by a set of indicators. These indicators are extracted from a knowledge base according to the location and the date. This knowledge base represents the knowledge of the indicators evolution only. For instance, the ship environment could be the weather conditions (state of the ocean), the seawater quality (salinity, temperature, etc.).

The environmental level (Fig. 7) goal is to break up the ship road book when the constraints imposed by the environment to the ship are considered as constant. A set of constant constraints define the environmental context. This level defines the schedule of the various environmental contexts Ec_j.

4.2 The Resources

The resources are subsystems necessary to achieve a mission successfully. They are identified from the functional analysis of the system. The decomposition level of the system into resources depends on the maintenance actions. This is useless to decompose a Diesel engine in intake manifold, turbo compressor, exhaust manifold, etc., if in failure mode, the complete Diesel engine is going to be replaced by another one.

Each resource is characterized by one or more use profile and degradation. A use profile of a resource corresponds to the mode in which the resource is solicited. For example, the constraints imposed to the ship propulsion are not the same when the ship in an acceleration phase or when the ship is navigating at its cruising speed. A degradation is linked to a physical phenomenon which evolves during the resource life. The degradation rate, which corresponds to the speed of the degradation evolution is assumed to be function of the use profile and the environmental context. For a given resource R_x, the various use profile are noted $Pu_{(R_x,k)}$ and the various degradation are noted $D_{(R_x,i)}$. The use of a resource is thus defined by the pair $\left(Pu_{(R_x,k)}, Ec_j\right)$. Each degradation $D_{(R_x,i)}$ is normalised between 0 and 1. The health indicator corresponding to $D_{(R_x,i)}$ is given by:

$$H_{(R_x,i)} = 1 - D_{(R_x,i)} \tag{1}$$

The global heath indicator of the resource R_x is thus defined by:

$$H_{R_x} = min\left(Hi_{(R_x,i)}\right) \tag{2}$$

To describe the evolution of $D_{(R_x,i)}$, a two step method is proposed. First, the evolution is defined qualitatively (Fig. 8), this step characterises the first and second derivative of $D_{(R_x,i)}$ ie. if the degradation is constant or evolves in a concave, convex or linear trajectory. In a second step, the evolution is defined quantitatively by the parameters α. On figure 8, various values of α are plotted for linear, convex or concave evolution. This plot requires the definition of the degradation by a set of functions given in table 1 where τ corresponds to the time.

Table 1. Quantitative description of degradation functions

Evolution	Sign of $\dot{D}_{(R_x,i)}$	Sign of $\ddot{D}_{(R_x,i)}$	$D_{(R_x,i)}$
Constant	0	0	$Cst.$
Linear	+	0	$\alpha\tau + Cst.$
Convex	+	+	$(\alpha\tau)^2 + Cst.$
Concave	+	-	$\sqrt{(\alpha\tau)} + Cst.$

Degradation $D_{(R_x,i)}$ is thus modelled by two matrices $\Psi_{(R_x,i)}$ and $A_{(R_x,i)}$ respectively the qualitative matrix (table 2) and the quantitative matrix (table 3).

Table 2. $\Psi_{(R_x,i)}$: the qualitative matrix

	Ec_{j_1}	Ec_{j_2}	$\dots$	Ec_{j_k}	$\dots$	Ec_{j_m}
$Pu_{(R_x,k_1)}$	++	00	$\dots$	+-	$\dots$	00
$Pu_{(R_x,k_2)}$	+-	+0	$\dots$	++	$\dots$	00
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Pu_{(R_x,k_n)}$	+0	++	$\dots$	+0	$\dots$	+-

Table 3. $A_{(R_x,i)}$: the quantitative matrix

	Ec_{j_1}	Ec_{j_2}	$\dots$	Ec_{j_k}	$\dots$	Ec_{j_m}
$Pu_{(R_x,k_1)}$	$\alpha_{1,1}$	$\alpha_{1,2}$	$\dots$	$\alpha_{1,k}$	$\dots$	$\alpha_{1,m}$
$Pu_{(R_x,k_2)}$	$\alpha_{2,1}$	$\alpha_{2,2}$	$\dots$	$\alpha_{2,k}$	$\dots$	$\alpha_{2,m}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Pu_{(R_x,k_n)}$	$\alpha_{n,1}$	$\alpha_{n,2}$	$\dots$	$\alpha_{n,k}$	$\dots$	$\alpha_{n,m}$

The degradation function is obtained by setting-up matrices $\Psi_{(R_x,i)}$ and $A_{(R_x,i)}$. Matrix $\Psi_{(R_x,i)}$ could be built by questioning the users of the system and sometimes using data analysis. When this matrix is validated the $A_{(R_x,i)}$ matrix can be built. If data are available parameters α could be learnt, else they could be initialized by expert. When the prognostic is different from the real resource state parameters α could be updated if real environmental context and real use profile are clearly identified.

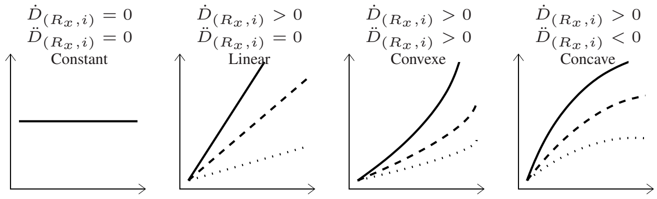

Fig. 8. Qualitative description of degradation functions

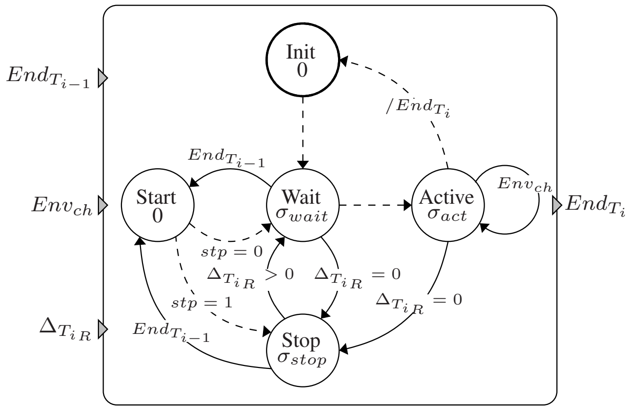

Fig. 9. Generic DEVS atomic model of a task

4.3 The Mission

The mission profile is necessary and very important in order to take the constraints applied to the resources into account. The mission profile is built by decomposing the mission into tasks. A task corresponds to the use of a set of a resource during a period of time. During a task, the used resources could have only one use profile. The mission profile is deterministic, it is known before the ship departure, and factual, the end of one task is the start of another one. Firstly, the mission level consists of building a task library according to the system. In this library, each task is defined by a set of couples $\left(R_x, Pu_{(R_x,k)}\right)$ i.e. how each resource is used during the task. The set of used resources of a task T_i is denoted T_{iR}.

To perform a prognostic it is necessary to model the profile mission in order to simulate it. A generic Discrete EVent Specification (DEVS) Atomic Model of a task (Fig. 9) is thus defined. DEVS is a modular formalism to model causal and deterministic system. A DEVS Atomic model is based on continous time, inputs, outputs, states, transition functions, output functions and state life time functions (Ziegler et al [2000]). More complex models are built by connecting several atomic models in a hierarchical way. Interactions between atomic models are ensured by the input and output ports.

The inputs of the generic task model are $End_{T_{i-1}}$ which is the end event of the previous task, the variable Env_{ch} corresponds to the change on environmental context and the variable $\Delta_{T_{iR}}$ which represents the availability of the resources used in the task T_i. When one or more resources are unavailable, $\Delta_{T_{iR}}$ is null. The output of the model is the end task event End_{T_i}. The initial state "Init" initializes the model variables $run = 0$, $stp = 0$ and the task life time l_i with the intended time. Then, the model is in phase "Wait" in order to wait for the event $End_{T_{i-1}}$ to pass in phase "Active". If in in waiting phase the event $\Delta_{T_{iR}=0}$ occurs. The task is stopped (phase "Stop"). The phase "Start" allows to memorize the event $End_{T_{i-1}}$ even if the task is stopped. As soon as $\Delta_{T_{iR}=1}$ occurs, the model is in phase “Wait” and if $run = 1$ goes to phase “Active”. “Init” and “Start” have a null life time, they are phases to update variables. For “Wait” and “Stop” phases the life time depends on variables run and stp:

- if $run = 0$ then $\sigma_{wait} = \infty$ else $\sigma_{wait} = 0$.
- if $stp = 0$ then $\sigma_{stop} = \infty$ else $\sigma_{stop} = 0$.

The life time σ_{act} is defined in section 4.4.

The complete mission model is then built by associating task atomic model where a task model is a generic DEVS model with one task of the library. Two tasks connectors are also defined in DEVS: the synchronization connector where two or more tasks have to be finished in order to begin a new task, and the delay connector corresponding to a delay in the event End_{T_i}.

4.4 Prognostic realization

The prognostic consists in the simulation of the mission model where Env_{ch} and tasks life time are initialized. During the phase “Active” of each running task, the resource level is used to project degradations ahead. The prognostic realization is presented through a fictive example.

Example definition: A ship is assumed to be composed of two resources R_1 and R_2 with one degradation to track respectively $D_{(R_1,1)}$ and $D_{(R_2,1)}$. The environment is classified in four contexts: $Ec_1, \ldots, Ec_4$. T_a, T_b, T_c, defined in table 5, correspond to the task library. Resources matrices are given in table 4.

Table 4. Resources definition

$\Psi_{(R_1,1)}$

	E_{c_2}	E_{c_4}
$Pu_{(R_1,1)}$	+0	++
$Pu_{(R_1,2)}$	00	+-

$\Psi_{(R_2,1)}$

	E_{c_1}	E_{c_2}	E_{c_3}
$Pu_{(R_2,1)}$	+0	++	+-

$A_{(R_1,1)}$

	E_{c_2}	E_{c_4}
$Pu_{(R_1,1)}$	$2.1O^{-5}$	$7.1O^{-5}$
$Pu_{(R_1,2)}$	0	$4.1O^{-5}$

$A_{(R_2,1)}$

	E_{c_1}	E_{c_2}	E_{c_3}
$Pu_{(R_2,1)}$	$1O^{-5}$	$1O^{-5}$	$2.1O^{-5}$

Table 5. Task library

T_a	$\left(R_1, Pu_{(R_1,1)}\right), \left(R_2, Pu_{(R_2,1)}\right)$
T_b	$\left(R_1, Pu_{(R_1,2)}\right)$
T_c	$\left(R_2, Pu_{(R_2,1)}\right)$

According to the ship objective, the mission is composed by the task sequence T_a, T_c, T_b with initial life times respectively 20, 10 and 25 time units (ut). Thus, the mission model can be built by coupling three generic atomic DEVS models and initialized the life time σ_{act}. The obtained DEVS model for the mission M_u is reproduced on figure 10 where the start of the first task is the mission begin event ($start$) and the end of the last task the mission end event (end). Tasks $T_{(u,k)}$ are defined by coupling a task of the library with a life time. For the simulation, the mission model requires the event Env_{ch} generated from the E_{C_j} sequence given by the environmental level. Table 6 gives the environmental context time table and so the event dates of Env_{ch} are 10, 25, 45 and 60 ut.

Table 6. Environemental contexts schedule

E_{c_j}	From	To
E_{c_1}	-5 ut	10 ut
E_{c_2}	10 ut	25 ut
E_{c_3}	25 ut	45 ut
E_{c_4}	45 ut	60 ut

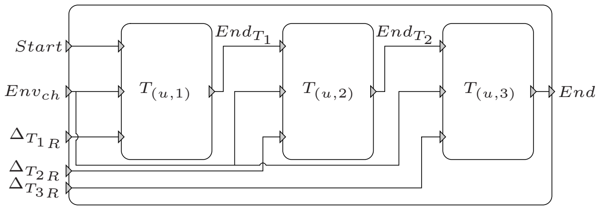

Fig. 10. DEVS model of the mission M_u

Prognostic function: This function is called when tasks arrive on phase “Active”. The degradation function for the degradation $D_{(R_x,i)}$ during task $T_{(u,k)}$ is denoted $D_{(R_x,i)}(T_{(u,k)})$ and for the mission M_u is denoted $D_{(R_x,i)}(M_u)$. When R_x is used by $T_{(u,k)}$ and matrices $\Psi_{(R_x,i)}$ and $A_{(R_x,i)}$ are defined for the current value of the environment context E_{c_j}, the variation of degradation function is given by:

$$\Delta D_{(R_x,i)}(T_{(u,k)}) = \left(\Psi_{(R_x,i)} \circ A_{(R_x,i)}\right)\left(T_{(u,k)}, E_{c_j}\right) \quad (3)$$

In the other case, the variation of the degradation function is considered as null. $\Delta D_{(R_x,i)}(M_u)$ is thus given by:

$$\Delta D_{(R_x,i)}(M_u) = \sum_{y=1}^{y=T(M_y)} \left(\Delta D_{(R_x,i)}(T_{(u,y)})\right) \quad (4)$$

where $T(M_y)$ is the task set ot the mission M_y. The degradation function $D_{(R_x,i)}$ during the task $T_{(u,k)}$ is the accumulation of the degradation variation for the previous task. It is given by:

$$\begin{aligned} D_{(R_x,i)}(T_{(u,k)}) &= D_{(R_x,i)_0} \\ &+ \sum_{y=1}^{y=u-1} \left(\Delta D_{(R_x,i)}(M_y)\right) \\ &+ \sum_{y=1}^{y=k} \left(\Delta D_{(R_x,i)}(T_{(u,y)})\right) \end{aligned} \quad (5)$$

with $D_{(R_x,i)_0}$ the degradation initial value. This value is in $[0, 1]$ according to the resource state when it is placed on the system. The degradation can also be defined as:

$$D_{(R_x,i)}(T_{(u,k)}) = D_{f\,(R_x,i)}(T_{R_x}^{-1}) + \Delta D_{(R_x,i)}(T_{(u,k)}) \quad (6)$$

where $D_{f\,(R_x,i)}(T_{R_x}^{-1})$ is the degradation value at the end of the last task where R_x is used. $T_{R_x}^{-1}$ is given by:

$$T_{R_x}^{-1} = T_{(v,w)},\ (v,w) = max(u,k) \text{ where } R_x \in T_{(u,k)\,R} \quad (7)$$

if the tasks set defined by $\left\{R_x \in T_{(u,k)\,R}\right\}$ is empty, the degradation value is on its initial value $D_{(R_x,i)_0}$.

During the simulation of the mission model variables, $\Delta_{T_{k\,R}}$ is a function of degradation states of resources used by task $T_{(u,k)}$. These variables are used to stop the mission at least once the resources used by the task become unavailable and they can also be used to update the task time l_k. The life time σ_{act} which represents the task time needs to be updated each time the task model arrives in phase “Active”. Thus, when the model arrives in phase “Active”, if the previous phase was also “Active” (ie event Env_{ch} occurs) l_k is given by:

$$l_k = l_k - \epsilon - f(\Delta_{T_{k\,R}}) \quad (8)$$

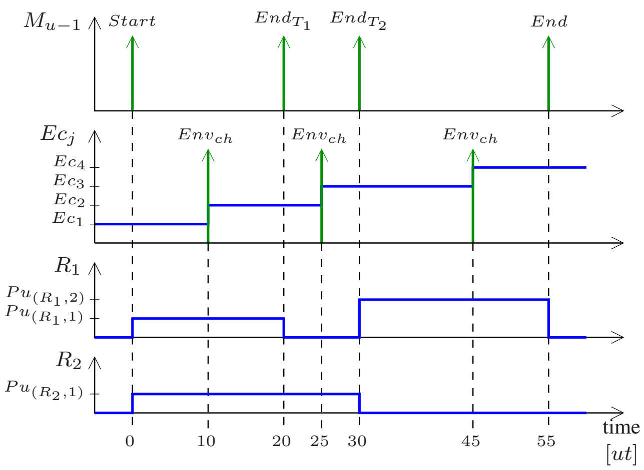

Fig. 11. Simulation of the mission M_u

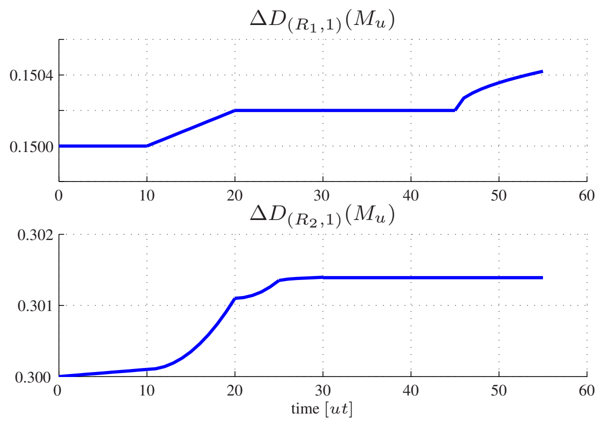

Fig. 12. Degradations variation during M_u

where ϵ , in DEVS, is the past time since the last event i.e. the remained time in phase "Active". l_k is also updated when the model arrives in phase "Stop" and the last phase is "Active". The life time σ_{act} for the task $T(u, k)$ is equal to l_k.

Application to the example: In this example, it is assumed that resources degradation states do not impact on the task time i.e. $f(\Delta_{T_{kR}}) = 0$. Moreover the degradation values at the end of the mission M_{u-1} are $D_{(R_1,1)_{M_{u-1}}} = 0.1$ and $D_{(R_2,1)_{M_{u-1}}} = 0.3$.

On figure 11, the simulation of the mission M_u is decomposed into tasks event on the first plot and environmental events on the second plot. The last two plots give the use of the resource during the mission. Figure 12 shows the evolution of resources degradation according to the environmental contexts and use profiles defined by the tasks (3). In this example, events linked to $\Delta_{T_{kR}}$ are not represented because it is a short mission where resources health indicators do not reach the fault threshold (see Fig. 2).

5. CONCLUSION AND FUTURE WORKS

In this paper, a new approach to prognostic system failure is presented. The decomposition of the system into three levels (mission, resources, environment) allows to take into account environmental constraints imposed to the system during a given mission. Moreover, the modelling of all types of resources degradations is made possible in a similar way whatever the resource (electrical, mechanical, digital, . . .)

In the example presented in this paper, only one prognostic is made. To have a more accurate prognostic various sequences of environmental contexts could be generated according to the ship road book. Each sequence will be balanced with its occurrence probability and mission will be simulated for each sequence. The prognostic will be thus given by an average of the prognostic of each sequence according to the environmental contexts sequence probability. Maintenance actions could also be modelled as a task which reduces the degradation state.

Future works will focus on the classification of environmental indicators in order to identify various environmental contexts and on the initialization of the qualitative and quantitative aspects of a ship. For a more realistic complex application, the dimensions of matrices Ψ and A may become very large , it could be interesting to firstly identify vectors of environmental contexts influence and use profile influence in order to then compute Ψ and A matrix.

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