

# A Procedure for Failure Prognostic in Dynamic Systems

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**Abstract:** In maintenance field, many developments exist to support the prognostic activity. However, the implementation of an adequate and efficient prognostic tool can be a non trivial task as it is difficult to provide effective models of dynamic systems including the inherent uncertainty of prognostic. In this context, the purpose of the paper is to propose a procedure to generate a prognostic model. The work is based on the integration of bond graph tool and Dynamic Bayesian Networks. The first one provides a dynamic model of the system, and the second ones, thanks to their inference capability, enable to take into account uncertainty and are well suitable to perform diagnosis and prognostic. The proposed procedure is illustrated on an hydromechanical system.

*Keywords:* Prognostic, Dynamic systems, Modeling, Dynamic Bayesian Networks.

## 1. INTRODUCTION

The growth of reliability, availability and safety of a system is a determining factor in regard with the effectiveness of industrial performance. As a consequence, the high costs in maintaining complex equipments make necessary to enhance maintenance support systems. Thus, traditional concepts like preventive and corrective strategies are progressively completed by new ones like predictive and proactive maintenances (Muller et al. (2008)). Thereby, prognostic is nowadays considered as a key feature in maintenance as the estimation of the remaining useful life of an equipment allows avoiding inopportune spending. From the research point of view, many developments exist to support the prognostic activity (Jardine et al. (2006)). However, choosing an efficient technique depends on classical constraints that limit the applicability of the tools: available data-knowledge, dynamic and complexity of the system, implementation requirements, available monitoring devices. Moreover, implementing an adequate tool can be a non trivial task as it can be difficult to build effective models of dynamic systems including the inherent uncertainty of prognostic. In this context, the purpose of the work is to propose a procedure to generate a prognostic model for dynamic systems. This work was led in order to respond to the need expressed by an industrial partner (em@systec) which develops an e-maintenance platform, and which is confronted to practical problems in implementing maintenance modules in real applications. Developments of this paper are founded on the following two assumptions. 1) In many cases, it is not too costly to equip dynamic systems with sensors. This allows gathering real data on-line. 2) Even if there is few *a priori* knowledge of the behavior of the system, it is all the more beneficial to try to build its analytical dynamic model. Thus, the proposed procedure is based on the integration of bond graph tool (BG) and Dynamic Bayesian Networks (DBNs).

The first one provides a dynamic model of the system (Karnopp et al. (1990)) and the second ones enable to take into account uncertainty and are well suitable to perform diagnosis and prognostic (Murphy (2002)).

The paper is organized in three main parts. In the first part, prognostic is defined and positioned within the maintenance strategies, and an overview of prognostic metrics and approaches is given. Following that, the methodology to build a prognostic model is explained in the second part. Finally, the proposed procedure is illustrated and discussed on an hydromechanical system.

## 2. PROGNOSTIC FRAMEWORK

### 2.1 Prognostic and Intelligent Maintenance Systems

Maintenance activity combines different methods, tools and techniques to reduce costs while increasing reliability, availability and security of equipments. Thus, one usually speaks about fault detection, failures diagnosis, and response development (choice and scheduling of preventive/corrective actions). Briefly, these steps correspond to the need, firstly, of "perceiving" phenomena, secondly, of "understanding" them, and finally, of "acting" consequently. However, rather than understanding a phenomenon which has just appeared like a failure (*a posteriori* comprehension), it is convenient to "anticipate" its manifestation in order to take adequate actions as soon as possible. This is what can be defined as the "prognostic process" and which is the object of this paper.

Industrials show a growing interest in prognostic which becomes a major research framework; see recent papers dedicated to condition-based maintenance (CBM) (Jardine et al. (2006); Ciarapica and Giacchetta (2006)). The relative positioning of detection, diagnosis, prognostic and decision / scheduling in the IMS (Intelligent Maintenance Systems) framework is schematized in Fig. 1.

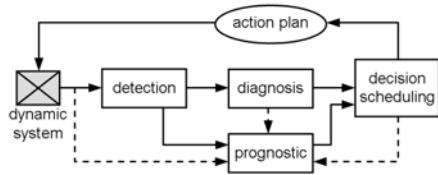


Fig. 1. Detection, diagnosis, prognostic and scheduling activities in IMS

Without distinguishing faults and failures in the paper, from the phenomenological point of view, the complementarity of detection, diagnosis and prognostic can be explained as follows (see Fig. 2):

- *detection* aims at identifying the functioning mode of the system, i.e., its current state,
- assuming that a failure occurred, *diagnosis* enables to isolate and identify the component that has ceased to operate (past propagation: from effects to causes),
- *prognostic* deals with the prediction of the future(s) state(s) of the system (future propagation: from causes to effects).

## 2.2 Prognostic concept

Although there are some divergences in literature, prognostic can be defined as proposed by the International Organization for Standardization: “prognostic is the estimation of time to failure and risk for one or more existing and future failure modes” (ISO, 13381-1 (2004)). In this acceptance, prognostic is also called the “prediction of a system’s lifetime” as it is a process whose objective is to predict the remaining useful life (RUL) before a failure occurs given the current machine condition and past operation profile (Jardine et al. (2006)). Thereby, two salient characteristics of prognostic can be pointed out:

- prognostic is mostly assimilated to a prediction process (a future situation must be caught),
- prognostic is grounded on the failure notion, which implies that it is associated with a degree of acceptability (the predicted situation must be assessed with regard to a referential).

Both levels of prognostic are distinguished for clarity of presentation but are however linked together in reality.

## 2.3 Prognostic metrics

There is no general agreement as to an appropriate and acceptable set of metrics that can be employed in prognostic applications, and researchers and CBM practitioners are still working on this (Vachtsevanos et al. (2006)). Various measures emerge however from literature and are

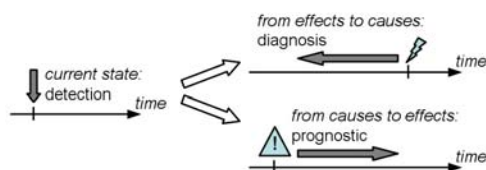


Fig. 2. Detection, diagnosis and prognostic - the phenomenological aspect

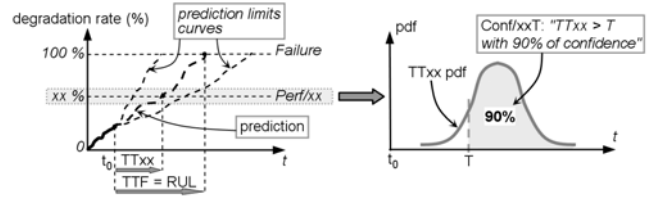


Fig. 3. TTF, RUL, TTxx and confidence measures

presented hereafter. As for any industrial task, prognostic can be evaluated at least in two ways:

- (1) the main objective of prognostic is to provide the efficient information that enable the underlying decision process, i.e., the choice of maintenance actions. Thus, a first set of metrics are those that quantify the risks incurred by the monitored system. This kind of metrics can be called the **prognostic measures**,
- (2) assuming that prognostic is in essence an uncertain process, it is useful to be able to judge from its “quality” in order to imagine more suitable actions. In this way, different indicators can be constructed: the **prognostic system performance measures**.

### 1) Prognostic measures

As mentioned earlier, the main prognostic measure pursued is the predicted time to failure (**TTF**), also called the remaining useful life (**RUL**). In addition, a **confidence** measure can be built to indicate the degree of certitude of the future predicted failure time.

By extension, and considering that practitioners can be interested on assessing the system with regard to any performance limit, RUL and confidence can be generalized: in Fig. 3, **TTxx** refers to the remaining time to overpass the performance limit Perf/xx, and **Conf/xxT** is the confidence with which can be taken the asset  $TT_{xx} > T$ .

### 2) Prognostic system performance measures

The **timeliness** of the predicted time to failure (TTF) is the relative position of the probability density function (pdf) of the prediction model along the time axis with respect to the occurrence of the failure event. This measure evolves as more data are available and reveals the expected time to perform preventive actions (Vachtsevanos et al. (2006)) (see Fig. 4). According to (Goebel and Bonissone (2005)), one needs to define two different boundaries for the maximum acceptable late and early predictions.

**Accuracy** measures the closeness of the predicted value to the actual one. It has an exponential form and is as higher as the error between the predicted value of TTF and the real one is smaller. **Precision** reveals how close predictions are grouped or clustered together and is a measure of the narrowness of the interval in which the remaining life falls. Precision follows from the variance of the predicted results for many experiments. Complementarity of accuracy and precision is illustrated in Fig. 5.

## 2.4 Prognostic approaches

Various prognostic approaches have been developed ranging in fidelity from simple historical failure rate models to high-fidelity physics-based models (Vachtsevanos et al.

(2006); Byington et al. (2002)). Required information (depending on the type of prognostic approach) includes engineering model and data, failure history, past operating conditions, current conditions, etc.

Similarly to diagnosis, prognostic methods can be associated with one of the following two approaches, namely model-based and data-driven. Each one has its own advantages and disadvantages, and, consequently, they are often used in combination in many applications.

**Model-based methods** Model-based methods assume that an accurate mathematical model for the analyzed system can be constructed. These methods often use residuals as features, and statistical techniques to define the thresholds that allow detecting faults. Several techniques are proposed in the literature to generate residuals: parity space, parameters estimation, observers, bond graph, etc.

The main advantage of these approaches is their ability to incorporate physical understanding of monitored system. In addition, in many situations, the changes in feature vector are closely related to model parameters (Chelidze et al. (2002)). A functional mapping between the drifting parameters and the selected prognostic features can be established (Luo et al. (2003)). Moreover, if the understanding of the system degradation improves, the model can be adapted to increase its accuracy and to address subtle performance problems. Consequently, they can significantly outperform data-driven approaches (next section). But, this closed relation with a mathematical model may also be a strong weakness: it can be difficult, even impossible to catch the system's behavior.

**Data-driven methods** Data-driven approaches use real data (like on-line gathered with sensors or operator measures) to approximate and track features revealing the degradation of components and to forecast the global behavior of a system. Indeed, in many applications, measured input/output data is the major source for a deeper understanding of the system degradation. Data-driven approaches can be divided into two categories: statistical techniques (multivariate statistical methods, linear and quadratic discriminators, partial least squares, etc.), and artificial intelligence (AI) techniques (neural networks, fuzzy systems, decision trees, etc.).

The strength of data-driven techniques is their ability to transform high-dimensional noisy data into lower dimensional information for diagnosis/prognostic decisions. AI techniques have been increasingly applied to machine prognostic and have shown improved performances over conventional approaches (Wang et al. (2004)). In practice however, it is not easy to apply AI techniques due to the lack of training data and of efficient procedures to

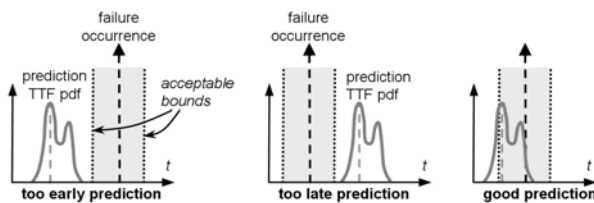


Fig. 4. Timeliness measure

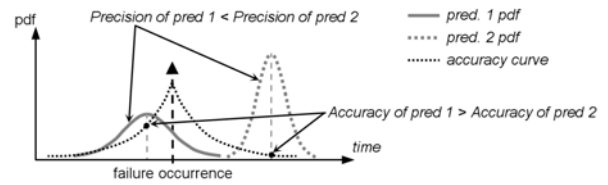


Fig. 5. Accuracy and precision measures

extract specific knowledge. Thus, data-driven approaches are highly-dependent on the quantity and quality of operational data.

### 3. PROCEDURE FOR PROGNOSTIC ON DYNAMIC SYSTEMS

#### 3.1 DBNs: a suitable prognostic tool

As stated in ISO, 13381-1 (2004) and mentioned earlier, prognostic aims firstly at estimating the remaining useful life of a system. Different methods can be used to provide this indicator but are restricted by the type and amount of available data, the necessity of building a model, etc. Secondly, prognostic tools must take into account the inherent uncertainty of prognostic to perform decisional metrics enabling the choice of maintenance actions: confidence, timeliness or accuracy.

Some techniques are well suited to deal with the aforementioned frame. For example, neuro-fuzzy systems proved to be adequate in forecasting applications under imprecision and uncertainty (Wang et al. (2004)). However, this kind of tools makes no assumption on the dynamic of the system (as they are based on a learning phase), and does not explicitly take into account the cause-effect relations. Yet, without being always necessary, it can be useful to represent the events causal dependencies in order to improve prognostic by considering diagnosis outputs. According to that, Dynamic Bayesian Networks (DBNs) (Murphy (2002)) are well suitable: their graphical representation and their inference capability make them appropriate for fault diagnosis (Lerner et al. (2000)) and prognostic (Muller et al. (2008)). Thus, the main objective of the reported work is to present a procedure to build a DBNs prognostic model for dynamic systems. This model takes into account the dynamic of the system, the sensors and monitoring data, the diagnosis outputs and also the on-line introduced maintenance actions.

#### 3.2 Prognostic procedure for dynamic systems

The proposed procedure is founded on the two following remarks. Firstly, when studying a dynamic system, it is possible and useful to represent its physical knowledge and dynamic behavior. This can be done by using bond graph (BG) tool. Secondly, as mentioned in section 3.1, DBN is a suitable prognostic tool. Thus, the present work aims at making a good use of both approaches by linking them for prognostic purpose. This can be done in 5 steps (Fig. 6):

- generate the bond graph model in integral causality,
- generate residuals from the bond graph model in derivative causality,
- construct the temporal causal graph (TCG) from the integral bond graph model,

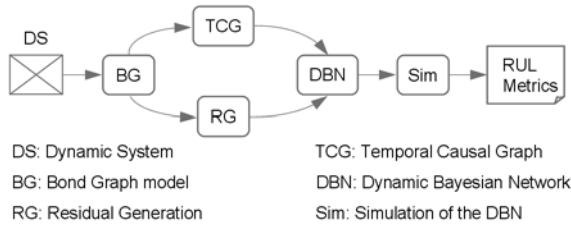


Fig. 6. Steps of the prognostic procedure

- generate the DBN by using the structure of the TCG and the residuals information,
- simulate the DBN to estimate the future state of the dynamic system and provide prognostic metrics.

The BG model is constructed from the dynamic system by representing the power transfer between the physical elements composing it (Karnopp et al. (1990); Paynter (1961)). The mathematical model of the system's behavior can be easily obtained from the BG model (in integral causality) in the form of transfer function or state space equations.

Residuals are generated from the derivative BG form which is preferred to the integral form for two principal reasons. 1) At the detection stage, the initial conditions are not always known which makes the integral calculation impossible. 2) In diagnosis phase, one observes the effect and tries to identify the cause (causal relations are inverted). In the proposed prognostic procedure, the generated residuals are used as monitoring features.

The temporal causal graph (TCG) is obtained from the bond graph model in integral causality of the dynamic system (Mosterman and Biswas (1997)). It is a topological representation that captures local dynamic relations between variables, and provides a more explicit representation of the relations between the system's parameters and the behavior variables (Lerner et al. (2000)). It also shows the algebraic and temporal constraints between the effort and flow variables of the BG model. In this paper, the TCG is used in order to build the DBN.

A DBN is a way to extend Bayes nets to model probability distributions over semi-infinite collections of random variables ( $U_t, X_t, Y_t$ ) representing the input, the hidden and the output variables of a state-space model (Murphy (2002)). DBNs generalize Kalman filters, hidden Markov models and hierarchical hidden Markov models, and allow users to monitor and to predict the future state of the system. The DBN related to the considered dynamic system is generated from the TCG by following the method proposed in (Lerner et al. (2000)).

At the simulation step, the DBN is parametrized by specifying the initial probability distributions of the nodes, and inference algorithms can be implemented in order to predict the future states of the system. Finally, the simulation results can be processed to provide prognostic metrics.

## 4. APPLICATION

### 4.1 System description

The procedure previously described is applied on an hydromechanical system (Fig. 7). It is composed of a valve, a

Table 1. Variables and parameters

Symbol	Designation	Unit
$P_m$	Fluid pressure at the input of the valve	$N/m^2$
$F_1$	Fluid flow across the valve	$m^3/s$
$P_1$	Pressure at the bottom of the tank	$N/m^2$
$R_2$	Hydraulic conductance	$m^4/s.N^{1/2}$
$F_2$	Fluid flow	$m^3/s$
$F$	Mechanical effort	$N$
$\omega_1, \omega$	Angular velocities	$rd/s$
$x_1$	Stem position of the valve	$m$
$\Gamma$	Torque	$N.m$
$m$	Mass of the stem in the valve	$kg$
$R_1$	Hydraulic conductance	$m^4/s.N^{1/2}$
$C_1$	Hydraulic capacity = $\frac{S}{\rho g}$	$m^4.s^2/kg$
$\rho$	Water density	$kg/m^3$
$S$	Cross section of the tank	$m^2$
$g$	Gravity constant	$m/s^2$
$k_1$	Stiffness	$N/m$
$b_1$	Friction coefficient	$N.s/m$
$k_2$	Stiffness	$N.m/rd$
$b_2$	Friction coefficient	$N.m.s/rd$
$J_1$	Moment of inertia	$kg.m^2$
$P_{atm}$	Atmospheric pressure	$N/m^2$

tank and a paddle wheel. The rotation of the paddle wheel is ensured by the flow of water leaving the tank from an orifice situated at the bottom of the tank. To maintain the paddle wheel at a given rotating speed, the amount of water in the tank is maintained at a constant level by acting on the stem position of the valve. The control system is not considered in the following developments. The nomenclature of the variables and parameters used in this application is given in table 1.

### 4.2 Generation of the Dynamic Bayesian Network

The bond graph model in integral causality of the hydromechanical system is given in Fig. 8. This model is derived from a word bond graph (Karnopp et al. (1990)) which is a bloc diagram showing the different powers exchanged between the physical components of the system. Four bond graph sub-models related to the valve, the hydraulic tank, the orifice and the paddle wheel are linked together. The mathematical model of the system can be obtained from the BG model in the form of a state space representation. This latter one allows to obtain the transition and observation matrices which are used in the final DBN.

The BG model previously built is used to generate the Analytical Redundancy Relations (ARRs) and the corresponding residuals. This is performed by applying the

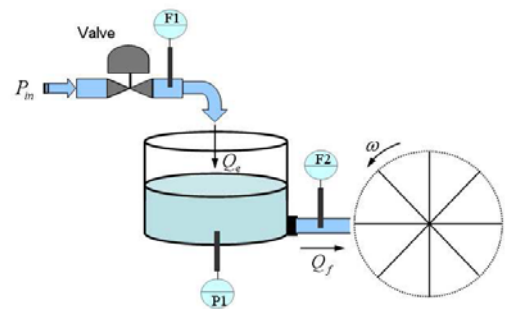


Fig. 7. The hydromechanical system

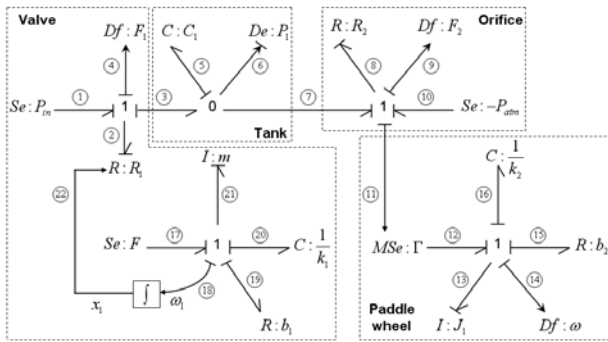


Fig. 8. The system's bond graph model

procedure presented in (Bouamama et al. (2003)). The main steps of this procedure are summarized hereafter:

- set the BG model in its derivative causality,
- write the equation of each junction of the obtained BG,
- eliminate the unknown variables from each equation,
- generate the ARRs, and by evaluating them, derive the corresponding residuals.

The unknown variables elimination process is achieved by following the causal paths, from known to unknown variables, on the derivative BG model. As a remind, an ARR is a constraint (or equation) between the system's known variables (measures, known inputs and parameters), whereas a residual is a numerical evaluation of an ARR (see B. Ould Bouamama et al. (2006) for more details). As the system is fully observable and does not contain any algebraic loop, and without considering its control part, five residuals can be generated (1 to 5).

$$r_1 = P_{in} - \frac{1}{R_1^2(x_1)} F_1^2 - P_1 \quad (1)$$

$$r_2 = F_1 - C_1 \frac{dP_1}{dt} - F_2 \quad (2)$$

$$r_3 = P_1 - \frac{1}{R_2^2} F_2^2 - P_{atm} \quad (3)$$

$$r_4 = k_2 \omega - \frac{d\Gamma_{\Phi(F_2)}}{dt} + b_2 \frac{d\omega}{dt} + J_1 \frac{d^2\omega}{dt^2} \quad (4)$$

$$r_5 = \frac{dF}{dt} - m \frac{d^2\omega_1}{dt^2} - b_1 \frac{d\omega_1}{dt} - k_1 \omega_1 \quad (5)$$

From the list of residuals, the fault signature matrix of the hydromechanical system can be simply built by analyzing the structure of each residual. This matrix is binary, containing in its rows the possible faults on the physical components and sensors, and in its columns the residuals. A "1" value in the fault signature matrix indicates that a residual  $r_i$  is sensitive to a fault in the corresponding component (represented by one or more parameters in the residual expression). In addition, two columns are added which indicate the detectability ( $D_b$ ) and isolability ( $I_b$ ) of each potential fault (table 2). A "1" value in the  $D_b/I_b$  means that a fault occurring on the corresponding physical component is detectable/isolable. Note that for this application, the faults are all detectable (the component's parameters are present in at least one residual), and isolable, except those of "Wheel" and "Sensor  $\omega$ ". The non-isolability of faults in these two components is due to

Table 2. Fault signature matrix

	$r_1$	$r_2$	$r_3$	$r_4$	$r_5$	$D_b$	$I_b$
Valve	1	0	0	0	1	1	1
Wheel	0	0	0	1	0	1	0
Tank	0	1	0	0	0	1	1
Sensor $F_1$	1	1	0	0	0	1	1
Sensor $F_2$	0	1	1	0	0	1	1
Sensor $P_1$	1	1	1	0	0	1	1
Sensor $\omega$	0	0	0	1	0	1	0
Sensor $\omega_1$	0	0	0	0	1	1	1

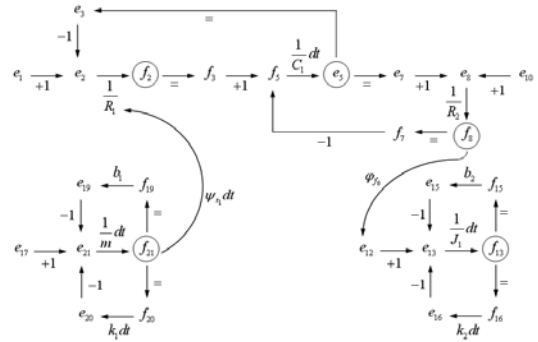


Fig. 9. The temporal causal graph of the hydromechanical system

the fact that they have a same signature.

The TCG of the hydromechanical system is given in Fig. 9, and is generated from the integral BG model of Fig. 8. The variables shown on this TCG are the generalized variables (efforts and flows) used in the BG model. The arrow from  $f_8$  to  $e_{12}$ , labeled  $\varphi_{f_8}$ , traduces the fact that the torque  $\Gamma$  acting on the paddle wheel is dependent on the flow of fluid coming from the tank. Similarly, the hydraulic resistance  $R_1$  of the valve depends on the stem position  $x_1$ , and this is represented by the arrow labeled by  $\psi_{x_1} dt$ .

The dynamic bayesian network of the hydromechanical system is given in Fig. 10. It is derived from the TCG by applying the method developed in (Lerner et al. (2000)). Three types of nodes are represented: observed nodes (shaded), hidden states and faults nodes. The variables and parameters used in the DBN are those of the TCG, and correspond to the BG generalized variables and system's parameters. In this application, three kind of drift faults are considered: an incipient fault in the valve (supposing that the hydraulic resistance of the valve changes during the time due to sediments deposit), a small leakage from the tank (assuming that this leakage can be represented by a change in the value of the hydraulic capacity  $C_1$ ), and a slow change in the structure of the paddle wheel. These faults are represented on the DBN graph by the nodes ( $D_{R_1}, R_1$ ), ( $D_{C_1}, C_1$ ), and ( $D_{J_1}, J_1$ ).

#### 4.3 Discussion

By following the proposed procedure, a DBN model for prognostic can be constructed. Parameters of this DBN are those of the physical system on which one can add noise, profiles of faults, measurements noises, and data provided by the monitoring and diagnosis systems (numerical values of residuals). On this basis, simulations on the DBN can be performed, by using inference algorithms proposed in (Murphy (2002)), in order to estimate the future state of the hydromechanical system and the prognostic metrics.

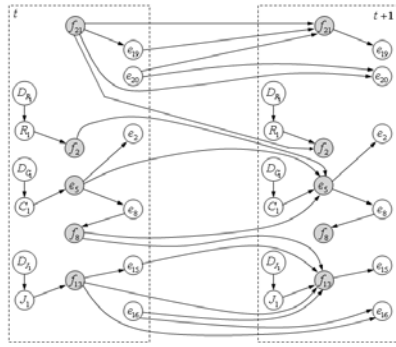


Fig. 10. The dynamic Bayesian network of the hydromechanical system

In practice, some processing on the residual signals are needed to detect earlier drifting faults. One way to do this consists in integrating the residual signals. Appropriate thresholds must also be defined so that when a residual exceeds its corresponding nominal value, an event is generated to update the related parameters of the DBN (for example, if an incipient leakage is detected, the value of the parameter  $C_1$  is modified). Again, simulating the updated DBN, one can estimate the future state of the system including these new observations (also called evidences).

## 5. CONCLUSION

Prognostic aims globally at estimating the remaining useful life of a system. However, building an effective tool to support this activity is not a trivial task: prognostic is intrinsically uncertain and prognostic tools must take this into account in order to perform decisional metrics enabling the choice of preventive actions. According to this, dynamic Bayesian networks are well suitable as they enable to consider the dynamic of the system as well as the inherent uncertainty of the prediction process. But, this supposes the construction of the DBN model. Thus, in this paper, a progressive procedure to build the DBN model for prognostic is proposed and illustrated on an hydromechanical system.

Developments are founded on the elaboration of the bond graph model that represents the dynamic behavior of the system. This model is then used to generate fault indicators (residuals) as well as the temporal causal graph which provides an explicit representation of the relations between the system's parameters and the behavior variables. Finally, the TCG serves to construct the DBN allowing to perform prognostic (RUL, confidence measures, etc.).

The proposed methodology is quite easy to follow and apply on small dynamic systems (mechatronic and hydromechanical systems for example). Moreover, the resulting DBN do not suffer from a learning process and is parametrized by including the physical understanding of phenomena.

Developments are at present extended to take into account real industrial constraints in a more closely manner. The generalization of the procedure on complex systems is being studied by decomposing them into small subsystems. Works are conducted with the objective of being integrated to an e-maintenance platform of a French industrial partner (em@systec).

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