Process model-based Dynamic Bayesian Networks for Prognostic

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Abstract – **The degradation checking of critical components is one of the efficient means to minimize the non expected stops of production system and to reduce its costs. In this purpose, a methodology is proposed to design a prognosis process taking into account the behaviour of environmental events (exogenous inputs). The main contribution is the development of the probabilistic model which is based on the translation of a preliminary process model into Dynamic Bayesian Network (DBN). Specifications are given to assure the coherence both of the translation and the resulted model. These requirements are formalized according to the NIAM/ORM method towards its semantic strength, clarity and stability. An application is proposed on a water heater system.**

I. INTRODUCTION

In today's market, companies have to well-maintain their production system to face fierce competition and satisfy customers which requires low-cost products or services of high quality to be delivered quickly [1]. Indeed maintenance plays a critical role in a manufacturing organisation's ability to maintain its competitiveness by contributing to the reduction of work-in-process inventory, the improvement of equipment reliability, and improved productivity, quality and product service [2]. In that way, maintenance is an essential factor to dynamically optimise the performances by reducing the "inefficiencies" … but only if maintenance evolves from traditional preventive strategies to just-in-time or proactive ones. The prognosis process which is the support of the anticipative role is often considered as the Achilles heel within proactive strategy. Most of the existing prognostic methods are component-oriented and without a real formalization in the modeling. It is now not sufficient to face the expected performances optimization with regard to the complexity of the plant where the degradation and deviation modeling is really difficult due to the economic or stochastic degradation dependencies among components.

In that way, this paper deals with the deployment of prognosis process based on a methodology described in section 2 which combines both a probabilistic approach for degradation mechanism modelling and an event one for dynamical monitoring. The implementation of the methodology is constrained by the DBN formalism which forbids the creation of cycle in the network as explained in section 3A. Thus, additional specifications are required to overcome this limitation. Theses specifications are formalized in section 3B according to the NIAM/ORM method. Then, a case study for a water heater system illustrates this work in section 4 before the brief conclusion drawn in section 5.

II. PROGNOSIS PROCESS DEVELOPMENT

This development is supported by the global methodology, more detailed in [3], and which is structured in three steps:

A. Process & Flow-based approach

The industrial system to be considered is modeled through functional analysis by using process approach [4]. One process is broken-up into several sub-processes, and the same mechanism is applied from the sub-processes until the expected level of abstraction is reached (e.g. component). The proposed definition of a process relies on four concepts interpreted as follow: Support which implements the process, the Goal which represents the purpose of the process, the Function which is a desired action and the Behavior which explains how a system does what it is intended to do. The behavior can be identified as: nominal (function realized), degraded (partial loss of the function) and failing (total loss of the function). The process behavior is described by the causal relationships between its inputs flows, the support, and its outputs flows. The concept of Flow-based performance evaluation means that the performance (goal's achievement) of a process can be directly measured on the produced flows and more precisely, on the value of its attributes.

B. Elaboration of the probabilistic network

The second step consists in transforming the previous process model into a probabilistic one which represents the causal relationships and temporal degradations in a unified way. The probabilistic model is developed by means of Bayesian Networks (BN) which offer interesting perspectives on knowledge representation and decision support system [5]. The model goal is to support the mechanisms of inference which can propagate, in the future, the process degradation and determine at every time the impact of this degradation on the whole system. The temporal degradation mechanisms are integrated to the probabilistic model by means of dynamic nodes [6]. Hence, the resulting network is a Dynamic Bayesian Network (DBN) which represents the joint probability distribution over all variables.

C. Design of the monitoring architecture.

The development of the monitoring architecture materialising the event approach is directly deducted from probabilistic model: each observable variable is associated to an indicator. The values of these indicators are refreshed with the current status of the shop floor data and controlled in real time by means of algorithms [7]. These events are displayed and stored in an operating knowledge database adapted to the refinement of the probabilistic model's parameters.

III. PROBABILISTIC MODEL DEVELOPMENT

The system modeled by Process & Flow-based approach is converted into a DBN according to several translation rules. The process model provides the information necessary to define the structure of the model. But it is not enough to create the DBN. Indeed, additional sources of knowledge are required to implement the translation Process/DBN:

- A FMEA (Failure Mode and Effects Analysis) provides the potential degradation of each support. In addition, this analysis provides the consequences of degradations on the system.
- A HAZOP (HAZard and OPerability) study (which consists in analysis the flows and the possible deviations of their attributes) allows, from a deviation on a flow property, to define its link with one degradation or failure of the process and/or system.
- Knowledge of the physical relationships which links input flows, support and output flows for each process.
- An operational database for the parameters learning if there is enough sufficient usage data. Otherwise, expert's knowledge is used to elicit the parameters in terms of subjective estimates.

A. Modeling stages

In fact, the translation process unfolds in three stages: the definition of nodes & states, the creation of the structure and the definition of the network's parameters.

1) Nodes and states: The dynamic Bayesian network nodes represent the supports and the flows of processes. A support is associated to several nodes which correspond to its potential degradation modes. A flow contains as many nodes as its related attributes. The basic idea is to identify each flow attribute with a "static" variable and each degradation mode with a "dynamic" variable. A support state is defined as a reachable combination of the states of its degradation modes M_i. A state of M_i is defined either by its physical meaning (e.g. oxidation or corrosion level) or by the consequence of the degraded state on the process performance (e.g. % loss of conductivity). The states of attributes correspond to the process performance allocation fixed by the company.

2) Structure: An edge is synonym of a conditional dependency between the variable that it links (e.g. the impact of the support's degradation on a produced flow). As the processes are linked together by their common flow (an output flow for the upstream process can be an input flow for the downstream process), the model structure consists in specifying a set of edges which represents the causal relationships between the inputs flows, the support, and the outputs flows. By default, each output flow attribute can have for parents every attribute of the input flow and every degradation mode of the related process.

3) Network's parameters: Each node has a Conditional Probability Table (CPT) that quantifies either causal or temporal relationships. Root nodes have only prior probability distributions modeling the statistics of extern input flows. For causal relationship, a conditional probability is affected to each instance of the output flow attributes considering each configuration of input flows and support. For a temporal relationship, the elicitation of conditional probability defines the deterioration (stochastic processes). In our case, these processes are represented by DBN model.

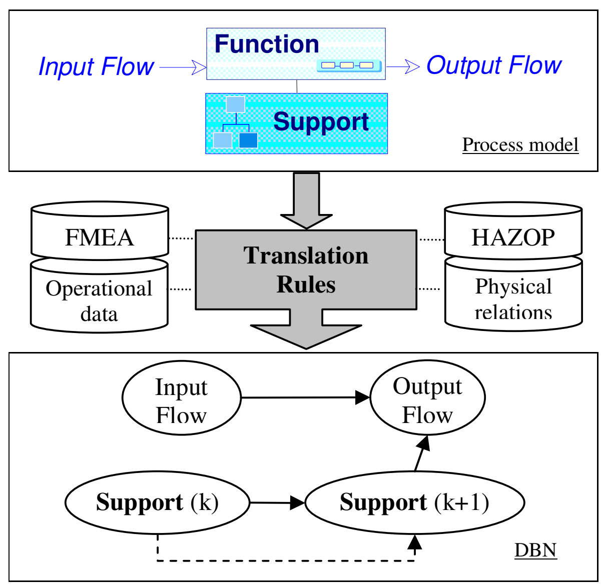

Fig. 1. Translation Process model / dynamic Bayesian network

B. Process model specifications

The dynamic Bayesian network used is based on an inference algorithm which forbids the cycle creation in the network. As it is presented in 2B, the main structure of the DBN comes from the structure of the preliminary process model. Therefore, there are two solutions to prevent the creation of cycle.

- The first one consists in defining particular restrictions on the process modeling in order to avoid that the designer can define a model with cycle.

- The second solution is based on the abolition of causality loop in the Bayesian network thanks to a set of rules which authorize arc deletion or change direction of some arrows [8]. However this manipulation leads necessary to the questioning of several dependence relationships stated by the process model. Consequently, this last strategy has been rejected.

The process approach we proposed is based on the concepts introduced by popular methods for functional modeling such as IDEF0 (called as well SADT). These methods describe and decompose the organization of systems in a structured graphical form. Only, the application of a method in a specific domain requires some adaptation, modification of the method to take into account the specificities of the domain. In our case, it implies that the process model must be established in regards of the prognostic finality and by considering the constraints induced by the DBN formalism.

1) The cycle problem: Whatever the situation, the creation of a cycle in the DBN results from a loop which already existed in the process model. So, it is important to understand when and why a cycle creation is possible in the process model. This situation occurs each time that a control loop is required to correct discrepancies between a measured process variable and the desired set point. As it is shown in Fig. 2, the loop "To control – Order – To transform – finished product – To measure – Product report – To control" provide irremediably the cycle "Order – finished product – Product report – Order" during the translation into DBN.

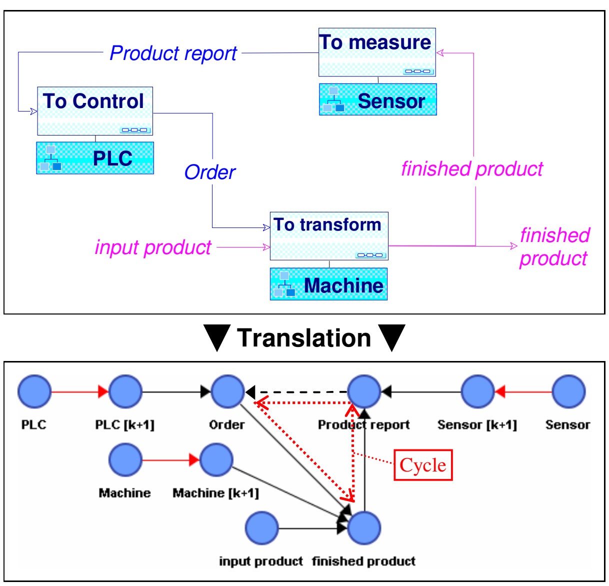

Fig. 2. Illustration of the cycle problem

2) The control loop interpretation: The process approach describes the manufacturing system functioning unless time consideration. In the previous example, an input product is transformed in a finished product according to an order which has been established thanks to the result of a measure done on the previous finished product. In fact there are two different finished product flows:

- The first one is the "current finished product". This flow represents the prognostic i.e. the expected state of the finished product taking into account to the behavior of the rest of the system
- The second one is the "previous finished product" which belongs to the previous production cycle. This flow represents the state of the finished product which has been measured by the sensor during the previous cycle product.

Thus, the process model contains flows which don't belong to the same temporal slice (the time unit considered here is the manufacturing lead time). These flows are different and so, they can't be represented and interpreted in the same way.

3) Necessary specifications: To distinguish the flows according to their temporal dimension, the more simple solution is to define a new flow characteristic:
- If the flow is related to the current manufacturing lead time, it is associated to the following designation: "flow (k+1)" or "flow" by simplification.
- Else, a flow subjected to a measure process and used to provide information about the previous state of the flow is defined as "flow (k)".
In fact, this manipulation consists in adding the temporal dimension not included in process approach.

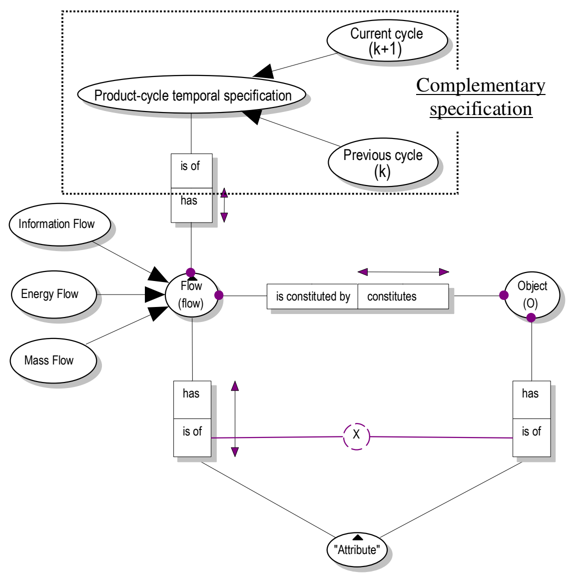

Fig. 3. Flow specifications

C. Formalization of the complementary specifications

The specifications of the process approach are formalized according to the NIAM/ORM method. Normally used on data modeling [9], NIAM/ORM provides intuitive diagrams which express the information in terms of elementary relationships between the objects of the domain. Its main advantages are the semantic strength, clarity, relevance and stability [10]. Actually, the strong point of NIAM/ORM is the possible validation or checking of the model by verbalization. The method has been implemented for instance to formalize normative knowledge in safety standards [11]. The tool VisioModeler[1] is used to develop the specifications.

The formalization of the process approach results in the elaboration of several ORM diagrams based on the general concepts described in section 2. The flow specifications diagrams represented Fig. 3 is the only one included in this paper. Its interpretation reveals that a flow (typed as Mass, Energy or Information) is composed of objects characterized by attributes. In addition, each flow is characterized by its product-cycle temporal specification: either (k+1) or (k).

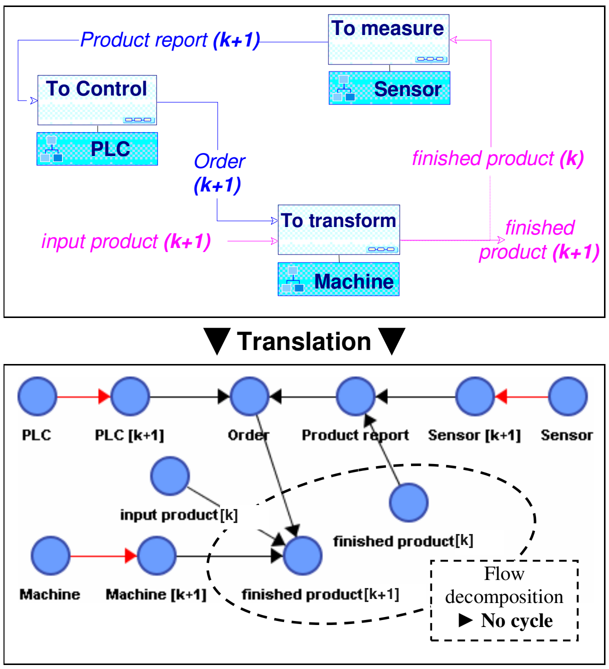

Fig. 4. Removal of cycle

The implementation of the specification on the previous example is described in Fig. 4. Contrary to Fig. 2, the DBN which results from the translation of the new process model does not contain cycle. The finished product flow is decomposed into two flows: finished product (k) which expresses the state of this flow during the previous cycle (k) and finished product (k+1) which is related to the present cycle (k+1).

IV. CASE STUDY

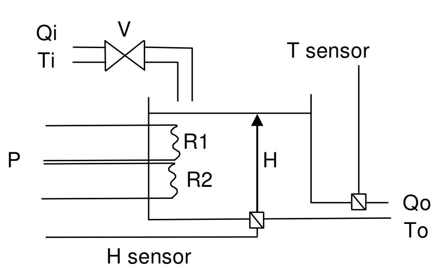

Fig. 5. Water heater physical process

The proposed method is applied to a water heater process depicted in Fig. 5. The goal of the process is to assure a constant water flow rate Qo with a given controlled temperature To. The function of the process "Water heater" is fulfilled by controlling the valve position and by heating the water in a tank. The sub-process is itself broken up into seven sub-processes implemented respectively by a component of the system (Fig. 7). The decomposition of the flows "Water to distribute" and "Water distributed and heated" according to their temporal dimension avoid the loop creation. In this way, the translation process is implemented without problem. It results in the DBN model described in Fig. 8. This model is a unified representation of all the knowledge formalised from the process model towards the dysfunctional analysis FMEA, HAZOP and the operational data.

In a strict sense, the DBN model contains one dynamic variable associated to each support i.e. it is assumed that each component is subjected to a single deterioration process. Take, as an example, the Heating resistors model. The dysfunctional analyses lead to identify 4 different states for this component. These states are defined according to their consequences on the process performance i.e. the maximum water temperature reachable by the system. The failing state (state 4) is achieved when *To=Ti*. The deterioration of the heating resistors is modelled by a Markovian process represented similarly by the DBN and the Markov Chain (MC) depicted in Fig. 6. The transition rates λ are defined *a priori* according to the operating knowledge available for similar resistors (it is assumed that these parameters are time-invariant) [12].

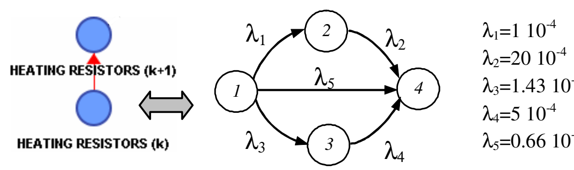

Fig. 6. Heating resistors DBN/MC model

The flows are represented by their attributes (Qo, To, H…). The prior probabilities attached to the input flow are fixed by default. For the other flows, the definition of the CPT relies on the elicitation of a conditional probability *p* to each instance of the output flow attributes, e.g. To, in each configuration of its parents variables (E.E, Heating resistors, Heating order and H level for To). The Software BayesiaLab is used for implementing the inferences mechanisms[2].

N.B. What is interesting in the DBN modelling is that DBN offers a factorised form of the traditional MC which normally suffers from a combinatory explosion of the states number [12]. In this case study, as each component have 2, 3 or 4 states, the MC model of the entire system would contain 1728 states while the DBN model is only composed of 25 nodes.

[1] Microsoft VisioModeler free software available on http://www.microsoft.com

[2] http://www.bayesia.com

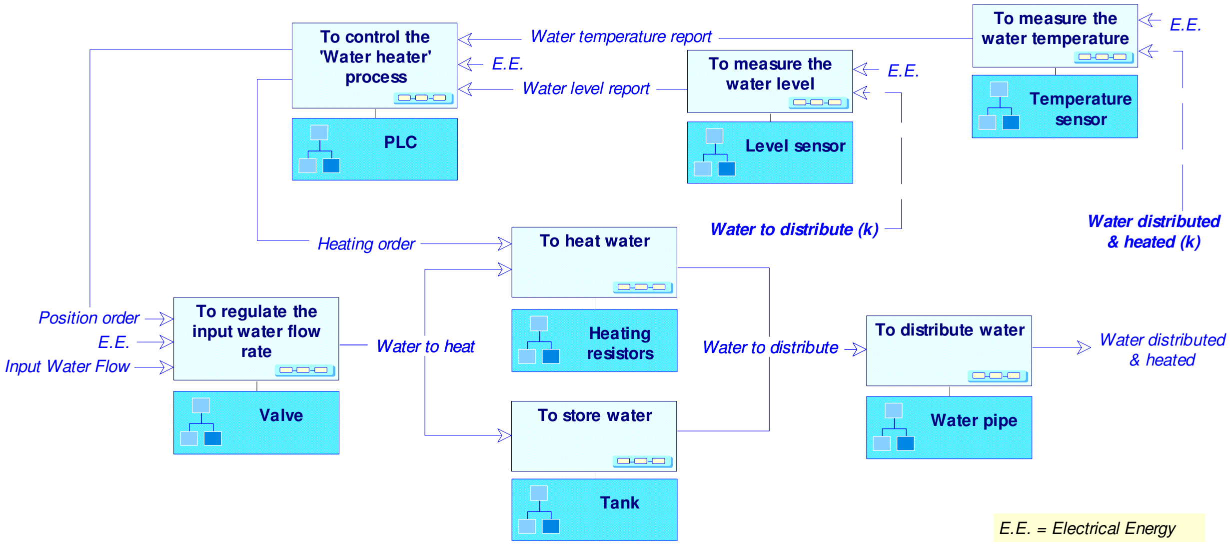

Fig. 7. "Water heater" process model

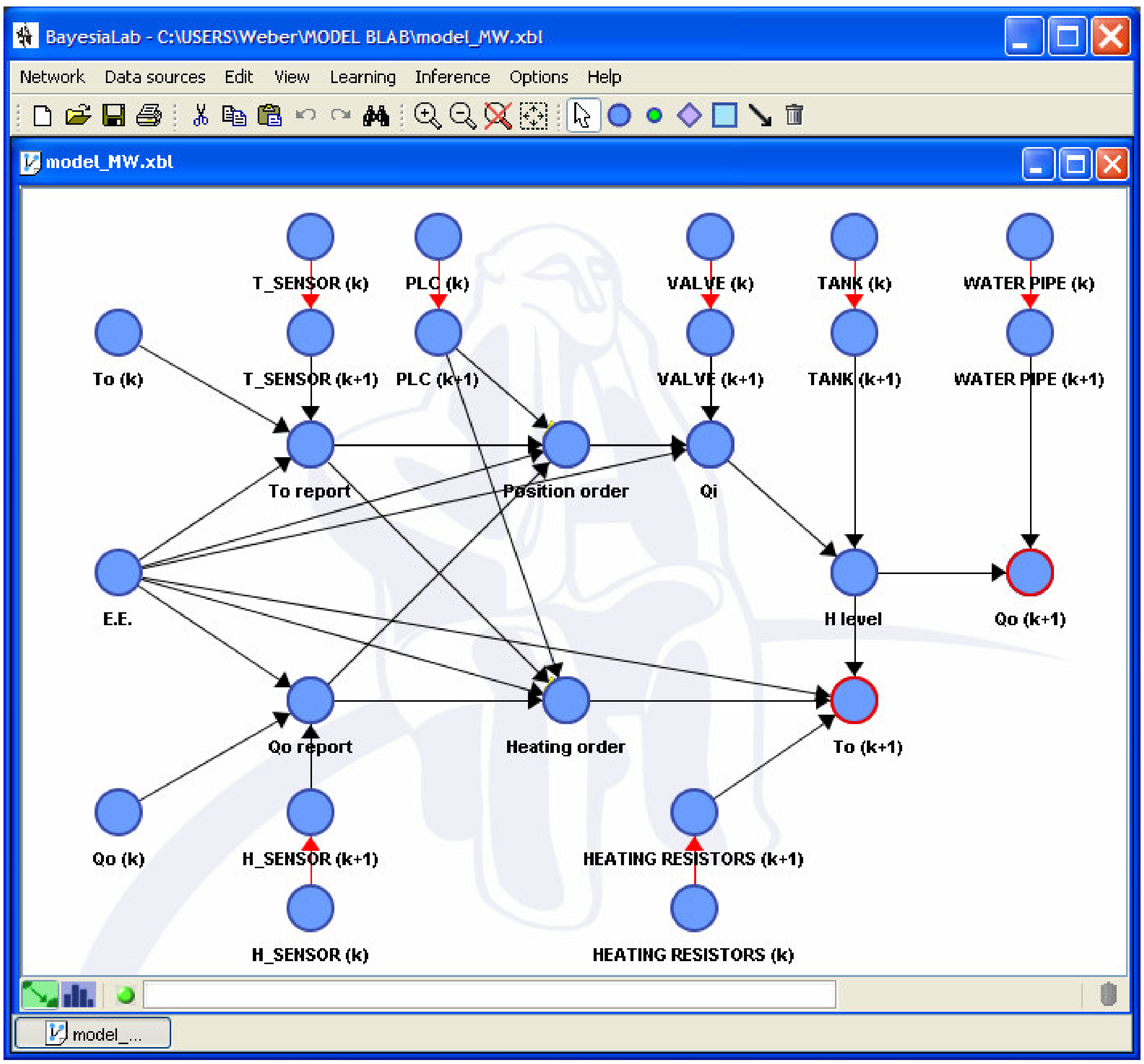

Fig. 8. “Water Heater” DBN model

Prognostic issued from prognosis process

The prognosis process is started in order to evaluate the expected temperature To and water flow rate Qo in the future given that all the components are new at time k=0. A maintenance intervention is simulated at k=1000 time unit. This action is assumed to be perfect i.e. the component is re-initialized in the nominal state.

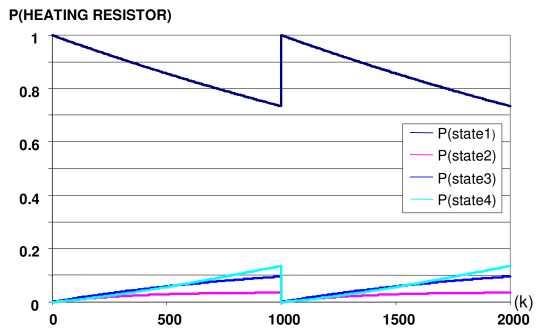

Fig. 9. Temporal degradation of the heating resistors

The temporal evolution of the probabilities related to the "Heating resistors" states is depicted in Fig. 9. This figure points out the impact of the maintenance action on the component behaviour. The propagation through the entire DBN model allows emphasizing the effect of this component degradation on the system performances. In this application, the performances of the system are evaluated directly on states of the two flow attributes To and Qo. Consequently, the temporal evolution of these parameters (shown in Fig. 10) can be considered as the forecasting of the system performances.
The impact of the maintenance action done on the heating resistors is visible on the temporal evolution on To but not on Qo which is not sensitive to this action because the level of water is controlled independently from the water temperature.

Finally, the concrete result of the prognosis process is a probability that the system reaches its finality at time k= 2000. The prognostic said that there is 21% chance that the Qo will be correct and 33% that To will be correct. This information can be propagated to another process (as an input data) or directly used by a decision process.

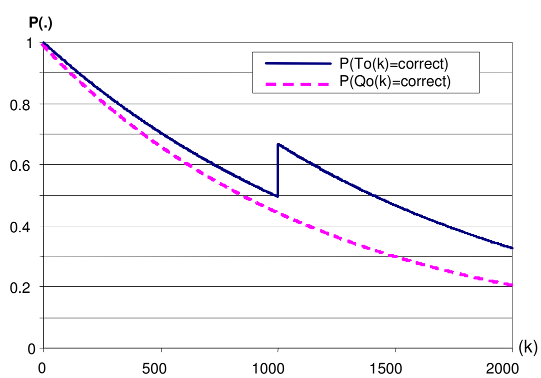

Fig. 10. Temporal evolution of the expected performances of the system

V. CONCLUSION & PERSPECTIVES

In regard of the work done in the maintenance and safety academic communities, the approach introduced is an added value on the systemic and dynamic visions of the degradation modeling. The work presented in this paper explains why a methodology supporting prognosis process modelling should be formalized to take into account the characteristics and the constraints induced by its modelling tool.
Moreover, the integration of the NIAM/ORM metamodel under MEGA Process[3] is in progress in our laboratory in order to develop a tool to assist the designer in developing its process & flow-based model. As a result any user would design a process model of his production system translatable automatically into DBN.

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