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Health Aware Control and Model-Based Prognosis

T. Escobet, V. Puig, and F. Nejjari

Abstract— **This paper presents a novel methodology named Health-Aware Control (HAC) system, that integrates System Health Monitoring (SHM), Control and Prognosis. This new approach based on both current and future health state estimates, provided by the prognosis module, takes into account the system's health information in the control objectives. In this way, the control actions are generated to fulfill the control goals and, at the same time, to extend the life of the system components. To illustrate the performance of the proposed approach, a conveyor belt system that uses an AC electrical motor to move a cart from one end to the other is used.**

I. INTRODUCTION

The safe and reliable operation of technological systems (cars, planes, trains, ...) and processes (energy, gas or water networks, chemical factories, ...) is of great interest and significance for human life and health protection, the environment, and the invested economic value. The correct operation of those systems has an important impact also on production cost and product quality in manufacturing. Maintaining the health of a complex system is a difficult task that requires the in-depth analysis of the target system, the principles involved and their applicability and implementation strategies.

The growing demand for improving the reliability and survivability of these systems and processes has led to the development of Prognosis and Health Management (PHM) and Fault-Tolerant Control (FTC) systems.

FTC systems are classified into passive and active. Passive FTC is designed to make the closed loop system robust against system uncertainties and some restrictive faults. In contrast active FTC reacts to system component failures actively by reconfiguring control actions so that stability and acceptable performance of the entire system can be maintained [1]. However, all these approaches lack of an active reconfiguration of the control law considering the health component prognostic information.

Prognostics and Health Management (PHM) is a methodology that permits the estimation of system reliability, the prediction of the remaining useful life (RUL) and the reduction of the inspection and maintenance efforts through real-time monitoring and incipient fault detection. The emergence and successful applications of PHM technology over the last decade, especially the development of on-line prognosis techniques, gave rise to a new category of FTC system, namely proactive FTC system [2]. Given accurate online prognostic information, proactive FTC system manages the accumulation of further damage through control actions.

This paper presents a novel methodology based on System Health Management (SHM) and Control. SHM integrates the tasks of diagnostic and prognostic modules, as well as processes and procedures responsible for information gathering about the system health enabling to make the right decisions on emergency actions and repairs [3]. On the other hand, Reliable Control (RC) tries to design control strategies to allow a safe and a reliable operation in spite of faulty situations [4]. As a result of this combination a new paradigm is proposed: the Health-Aware Control (HAC) system. In this paradigm, the information provided by the prognosis module about the component system health allows modifying the controller in such a way that the system health is considered in the control objectives. In this way, the control actions will be generated not only to fulfill the control objectives but also to extend the life of the system components.

HAC permits adjusting the controller even when the system is still in non-faulty situation. The prognosis module that is included in the HAC scheme will give an on-line estimation of the component aging and will allow not only fault accommodation, but also fault mitigation via proper control actions.

This approach allows mitigating or at least to avoid a catastrophe or a big damage of the system in the case of the occurrence of a severe failure. This is achieved by combining the current and the estimated future condition of the system.

To illustrate the performance of the proposed approach, a conveyor belt system that uses an AC electrical motor to move a cart from one end to the other is used.

This paper is organized as follows. In Section II, HAC paradigm is introduced and HAC architecture is given. Section III presents the prognosis module and introduces a method of RUL prediction. In Section IV, the performance of the proposed approach is tested by its application to a conveyor belt example. Finally, Section V summarizes the main conclusions.

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II. HEALTH-AWARE CONTROL

A. *Introduction*

Traditional control system design focuses on stability and performance only. In other words, the control design process ignores the effects of aging, fatigue, and damage in the components involved. On the other hand, as discussed in the introduction, the HAC uses the information provided by the prognosis module about the component system health to adapt the controller accordingly in order to extend the RUL of the system. In this way, the control actions will be generated to fulfill the control objectives and, at the same time, to extend the life of the system components. HAC control, contrarily to FTC, adjusts the controller even when the system is still in non-faulty situation. The prognosis module will estimate on-line the component aging for the specific operating conditions. In the non-faulty situation, the control efforts are distributed to the system based on the proposed health indicator.

Seminal ideas about HAC have already been suggested by [5], [6] and [7] that combine reliability and control and were known as reliable control. However, since at that time prognosis was still not a mature area, the HAC approach was fully developed. The main reason is that a lot of emphasis was put on diagnosing the fault and reconfiguring/ accommodating the control leading to the development of the FTC. However, industry is more concerned about managing appropriately the system health before the fault appears than in applying FTC methods once the fault has already appeared. This fact, additionally to the recent development of prognosis methods and techniques, has motivated the appearance of HAC. Some authors as in [10] have included RUL predictions in FTC strategies. In particular in this paper, when a fault is detected the RUL requirements are checked to assess if the mission can be accomplished without control reconfiguration. If not, a model predictive control strategy is used for control reconfiguration.

B. *Health-Aware Control Architecture*

The proposed architecture of HAC scheme is presented in Fig. 1 showing the integration of health monitoring, prognosis and control. It consists of four modules:

- Data acquisition and pre-processing.
- Condition monitoring and diagnosis.
- Prognosis.
- Decision-making.

These modules are not autonomous and the information is transferred from one to the other. In Fig. 1, the main interactions between the different modules are shown. Component failures and degradations lead to safety of critical situations in many processes. In the proposed architecture, system health monitoring methodologies have been integrated with control with the goal of maintaining the health status of the system and activating remedial actions (as, f.e., set-point adaptation, virtual sensors or actuators) when problems (faults or degradations) in sensor or actuator health are detected [8].

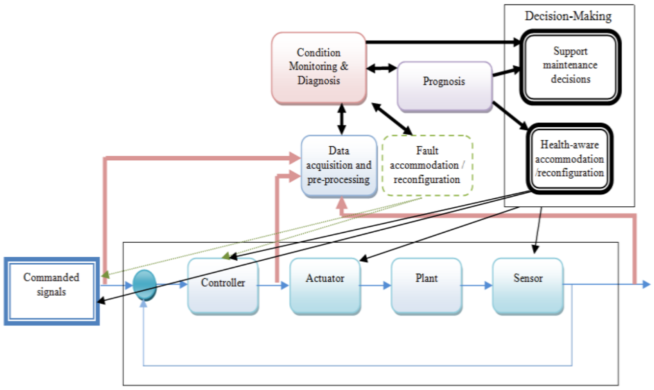

Figure 1. General architecture of HAC

In the next section prognosis is described. The strategies used for condition monitoring and support decision are introduced in [9].

III. PROGNOSIS MODULE

A. *Introduction*

The aim of the prognosis module is to provide users with an integrated view of the health state of the overall system and it is the main component of the PHM system. In generally, PHM systems incorporate functions of condition monitoring, state assessment, fault or failure diagnostics, failure progression analysis, prognosis and operational decision support [11]. Three aspects are necessary for prognostics to be effective: the ability to estimate the current state of the system, the ability to predict future state, and thereby time to fail, and the ability to determine the impact of the assessment on system performance and the need for corrective or mitigating action.

As with diagnostic, prognostic may be implemented using approaches that are either model-based or data-driven [12]. The model-based approach typically involves building mathematical models to describe both the physics of the system (including the interactions between components) and physical failures, such as crack propagation or thermo-mechanical degradation. Data-driven approaches attempt to derive models directly from runtime data collected. They are based on the assumption that the statistical characteristics of the system data kept relatively invariant until a fault occurs, and the anomalies, trends or patterns allow determining the state of health of a system. In this approach, collected data are analyzed using a variety of techniques, as statistical pattern recognition and machine-learning, which are used for both detecting changes in parameter data and making predictions.

In general, a good prognostic system must provide an accurate and precise estimation of the *end of life* (EoL) and *remaining useful life* (RUL) prediction and, also, specifying the level of confidence considering all the uncertainties. An extended summary of the approaches used in the case of rotating machinery can be found in [13].

A. *RUL prediction*

In general, prognostic methods use one or several measures of system current damage state, to track the degradation measure of the system and to predict the RUL. The degradation measure value ξ can be arbitrary. But, generally, to facilitate the analysis, the scaled measure ξ takes values in the interval [0,1] where it is assumed that failure occurs if ξ≥1. The RUL is then given by:

$$RUL_k = \hat{t}_{EoL} - t(k) \tag{1}$$

where $\hat{t}_{EoL}$ is the prediction of remaining life or the estimated time for meeting the specified performance (ξ=1) and $t(k)$ is the current time.

Prediction of the remaining life can be obtained on-line when it is assumed that the future operation of the system will follow the observed history of the system state and the dynamic of the mode changes. The architecture proposed to compute the RUL is presented in Fig. 2. It has two sub-modules: a model estimator and a RUL predictor.

Condition monitoring system provides the prognosis module with the main characteristics extracted from the system (f.e. parameters estimation, means of variables). Each one of the extracted features produces a time series. The stored data are used firstly for their fitting models, and then the model fitted is used for forecasting its evolution in the future.

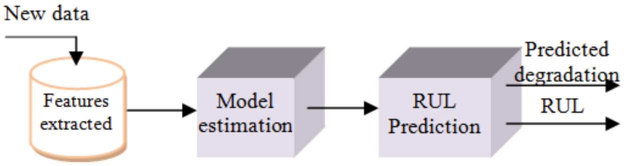

Figure 2. Prognosis module.

Giving a time series, $y(k)$, modeled by an Autoregressive (AR) model written in state space form:

$$\begin{aligned} \mathbf{x}(k+1) &= A\mathbf{x}(k) + K\varepsilon(k) \\ y(k) &= C\mathbf{x}(k) \end{aligned} \tag{2}$$

with **x**(*k*) is the state vector of dimension $na\times 1$, *ε* is white noise associated with *y*, and

$$A = \begin{bmatrix} a_1 & \cdots & a_{na-1} & a_{na} \\ 1 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 1 & 0 \end{bmatrix},\ K = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix},\ C = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix},$$

being a_i the model coefficients.

The *na* parameters of the system could be estimated using recursive least-square (RLS) method that minimizes: $V_\varepsilon(k) = \left(y(k) - \hat{y}(k)\right)^2$, where $\hat{y}$ is the estimated value computed by: $\hat{y}(k) = C\hat{A}\mathbf{x}(k-1)$ and V_ε is the residual variance; $\hat{A}$ denotes the space state matrix with the estimate values of the parameters.

The estimated AR model is used for variable multi-step prediction. The $\hat{y}$ and $\hat{V}_\varepsilon$ on an *h* horizon can be computed by:

$$\begin{aligned} \hat{y}(k+h|k) &= CA^h\mathbf{x}(k) \\ \hat{V}_\varepsilon(k+h|k) &= \sum_{p=1}^{h} CA^p K V_\varepsilon(k) \end{aligned} \tag{3}$$

Equation (3) allows for each $\hat{y}(k+h|k)$ to compute the standard deviation, denoted by $\sigma(k+h|k)$,

$$\sigma(k+h|k) = \sqrt{\hat{V}_\varepsilon(k+h|k)} \tag{4}$$

By considering a Gaussian distribution of the estimation error, a bounded envelope of the estimation of 95% can be computed on-line by using the following equations at the prediction time *h*:

$$\begin{aligned} \hat{y}(k+h|k)_{\boldsymbol{min}} &= \hat{y}(k+h|k) + 2\sigma(k+h|k) \\ \hat{y}(k+h|k)_{\boldsymbol{max}} &= \hat{y}(k+h|k) + 2\sigma(k+h|k) \end{aligned} \tag{5}$$

The lower and upper boundary of the expected time of failures, $RUL_{\boldsymbol{max}}$ and $RUL_{\boldsymbol{min}}$ respectively, can be computed as follows:

$$\begin{aligned} RUL_{k,\boldsymbol{min}} &= \hat{t}_{EoL,\boldsymbol{min}} - t(k) \\ RUL_{k,\boldsymbol{max}} &= \hat{t}_{EoL,\boldsymbol{max}} - t(k) \end{aligned} \tag{6}$$

where $\hat{t}_{EoL,\boldsymbol{min}}$ and $\hat{t}_{EoL,\boldsymbol{max}}$ are the estimated time for meeting the specified performance from the lower and upper envelopes (trajectories of $\hat{y}(k+h|k)_{\boldsymbol{min}}$ and $\hat{y}(k+h|k)_{\boldsymbol{max}}$) respectively, or equivalently:

$$\begin{aligned} \hat{t}_{EoL,\boldsymbol{min}} &= \left\{h \middle| \hat{y}(k+h|h)_{\boldsymbol{min}} = \xi\right\} \\ \hat{t}_{EoL,\boldsymbol{max}} &= \left\{h \middle| \hat{y}(k+h|h)_{\boldsymbol{max}} = \xi\right\} \end{aligned} \tag{7}$$

as it can be seen in Fig. 3. At time *k*, the estimated *RUL* belongs to the interval $R_{RUL,k} = \left[RUL_{k,\min}, RUL_{k,\max}\right]$ with 95% of confidence.

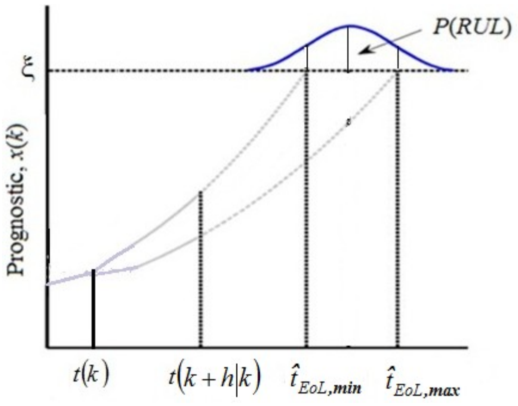

Figure 3. RUL prediction

IV. APPLICATION

A. System description

The proposed HAC approach and architecture can be applied to different kind of systems such as batch systems, hybrid systems (i.e., systems that can change their structure depending on operating conditions), manufacturing cells, among others. In this chapter, this architecture has been applied to a conveyor belt [9]. This conveyor belt uses an AC electrical motor to move a cart from one extreme to the other (Figure 4). The motor speed is controlled using a PI controller and a driver that has an encoder with two input channels. The velocity set-point is composed of an acceleration ramp, a constant value and a deceleration ramp. The available analog sensors measure AC motor current, motor temperature, driver temperature and encoder signals. This system has also four logical sensors located in the belt and in the cart for security purposes and two control signals to move the motor to the right or to the left. The SHM has been implemented in the integrated development environment LabWindows CVI 9.0 working on a Windows platform. The system has been designed using the multithreading methodology and the CompactDAQ-9172 system acquisition of National Instruments [9].

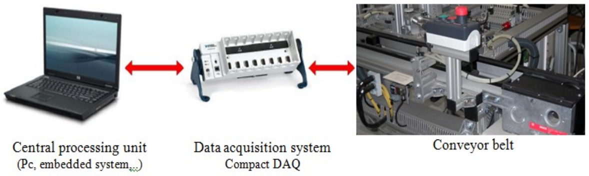

Figure 4. Experimental test-bed.

B. Data acquisition and pre-processing implementation

To ensure the integrity of the data used for prognostic purposes, the data acquired should be preprocessed and validated. The data generally come from the sensors or intermediate equipment, using a communication bus, either through a wireless (in the case of remote sensing and measuring) or standard buses. This can be the cause of a number of problems that the data received could suffer: non-constant sampling time, missing data, incorrect values and so on. These problems may be caused by communication problems or by sensor faults.

The on-line validation is done in the pre-processing module and allows calculating the quality index. Each variable is evaluated at two levels:

- Level 1: It checks whether the data stored in the buffer have the expected number of measurements. The relationship between actual and expected measurements indicates the quality of the data. If there are no data, a communication problem is reported.
- Level 2: It verifies if each data is between a maximum and minimum value. Any data out of this range is considered invalid.

Data is considered valid once passed the two validation levels. If level 2 or level 1 are not passed the quality of the data is marked as invalid because of sensor or communication problems, respectively.

Validated data are stored to be used by condition monitoring module.

C. Prognostic implementation

As the test-bed works cyclically, the condition monitoring system allows extracting the main features per cycle of work being some of them motor temperature, conveyor speed at constant velocity, peaks of intensity during acceleration, deceleration and slow down time. Prognostic module only works when new data are stored.

The prognostic methodology described in Section III has been implemented in LabVindows platform and works on line with the system. Algorithm verification has been performed in the laboratory. In order to evaluate the conveyor belt performances in degraded situations, several scenarios have been conducted forcing the working conditions. One of them has been done increasing the belt friction. In these conditions, prognostic strategy has been used to predict the temperature of the motor.

Figure 5 shows the temperature evolution and its prediction using the method presented in Section III starting at cycle 41 and using a forgetting factor of 0.9. The pre-established threshold is of 65% of the critical value. Notice that the prognosis follows the data trend. In this figure crossed blue line represents the real feature data; green line establishes the hazard threshold value, which is 0.65; the solid blue line indicates the nominal prediction computed using (3); and discontinuous red lines delimit the upper and lower predicted envelopes, using (5), with the 95% confidence bounds of system health. In this figure, the temperature evolves slowly over time. Figure 6 shows all the RULs computed from k=25 to k=100, the red continuous line shows the actual RUL; upper and down RUL prediction are marked with 'o' and '*' respectively. In Fig. 6, it can be seen that the proposed method applied to temperature evolution allows predicting in advance the evolution of RUL. In this study case, the actual RUL is 100 cycles.

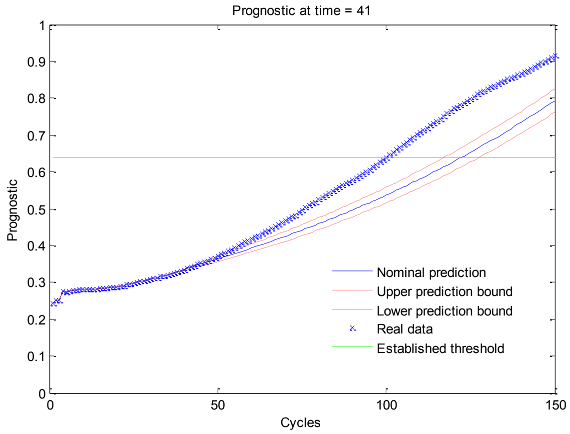

Figure 5. Temperature prognosis started from cycle 41.

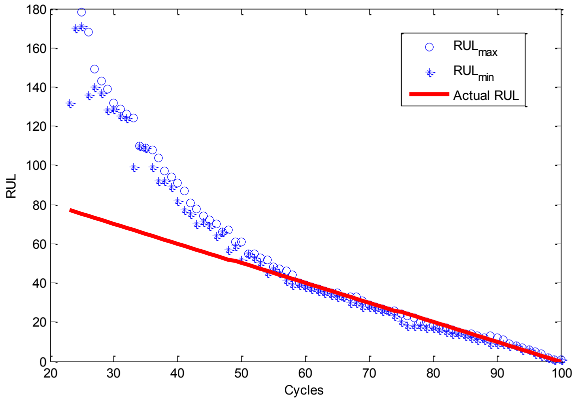

Figure 6. Experimental test-bed

D. *HAC implementation*

From the variables evaluated in the prognosis module, there are variables like the temperature that are critical and should be below some pre-established thresholds for safe operation. These critical variables are used in HAC in order to extend the system actuator life. In the conveyor belt case study, the temperature forecast has been used to implement a control reconfiguration strategy for the velocity PI controller in order to maintain the temperature T in a region of admissible behaviors. The controller set-point is adapted in function of predicted $R_{RUL,k}$ (6). *Algorithm 1* summarizes the proposed strategy to find the new set point value, SP_{new}, depending on the corrective action, ca, that increases or decreases with a prefixed slope, $\gamma_0 \in [0,1]$, taking into account the set $R_{RUL,k}$.

Defining a critical RUL band, $R^{crit}_{RUL} = \left[RUL^{crit}_{\min}, RUL^{crit}_{\max} \right]$ where the system should be kept operating until repair, at each time k it is checked if the critical RUL band intersects with $R_{RUL,k}$. If $R_{RUL,k} \cap R^{crit}_{RUL} = \varnothing$, and if $R_{RUL,k}$ is lower than R^{crit}_{RUL}, *Algorithm 1* reduces iteratively the velocity set-point. Otherwise, it enlarges it. Similar results could have been obtained keeping the original set-point but setting the integral action to zero (K_I=0) and decreasing the proportional gain K_P of the PI controller. Other control strategies, such as optimal or predictive control, could easily be used in the problem formulation such the computation of the control law takes into account the prediction of critical variables in order to prevent components degradation.

Algorithm 1. HAC strategy

```
Require: $R_{RUL,k}$, $R^{crit}_{RUL}$, $SP(k)$, $ca(k)$, $\gamma_0$
Default parameters $ca(0)=1$, $\gamma_0=0.01$
if ( $R_{RUL,k} \cap R^{crit}_{RUL} = \varnothing$ )
    if $RUL_{k,max} \le RUL^{crit}_{min}$ then
        $\gamma = -\gamma_0$.
    else
        $\gamma = \gamma_0$.
else
    $\gamma = 0$.
$ca(k) = ca(k-1) + \gamma$.
if ($ca(k) > 1$) then
    $ca(k) = 1$.
if ($ca(k) < 0$) then
    $ca(k) = 0$.
$SP_{new}(k) = SP(k) \cdot ca(k)$.
return $SP_{new}(k)$.
```

V. CONCLUSION

This paper has proposed the combination of system health monitoring with control and prognosis by the introduction of the HAC paradigm. In this paradigm, the information provided by the prognosis module allows modifying the controller such that the control objectives consider the system health. In this way, the control actions are generated to fulfill the control objectives and at the same time to extend the life of the system components. The prognosis module estimates on-line the component aging for the specific operating conditions. In the non-faulty situation, the control efforts are distributed to the system based on the proposed health indicator. The HAC system has been applied successfully to a conveyor belt system that uses an AC electrical motor to move a cart from one extreme to the other. However, some issues concerning the proposed HAC scheme could be improved. The health information is included in the controller design in an "ad-hoc" way, an improvement could be to do it in a systematic way. Another issue is the mathematical formulation of the interaction between prognosis and control that establishes a new feedback loop. This will enable understanding the effect of this loop in the whole performance of the system using techniques coming from hybrid system theory because of the combined discrete-event/continuous nature of the reconfiguration/ accommodation actions and the control loop, respectively.

ACKNOWLEDGMENT

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