PHM Techniques for Condition-Based Maintenance Based on Hybrid System Model Representation

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ABSTRACT

Condition-based maintenance (CBM) is a maintenance strategy that uses diagnosis and prognosis to determine system's health. The overall objective of this paper is design a real-time monitoring system for CBM, applied to a conveyor belt system, based on the integration of prognosis and health management technologies (PHM) and hybrid models. This work is focus on the prognosis part of PHM. A forecasting model based in Adaptive-Network-based Fuzzy Inference Systems (ANFIS) combined with a Gray-Scale Health Index (HI) is implemented to evalualte the system degradation. As shown throughout the paper, the hybrid model allows extracting the main features of the system that will be used in the prognostic algorithm. The obtained results show that the ANFIS prediction model linked to the degradation index HI can track the system degradation, thus have the potential for being used as a tool suitable for condition-based maintenance. [1]

1 INTRODUCTION

The present work is motivated by the increasing dependence of modern society on autonomous and complex technological processes and systems, where availability, reliability and safety are strategic words in industry. To achieve these requirements maintenance, or more general system's health monitoring, becomes an essential part. The performance degradation of mechanical systems is mainly due to component wear, abrasion and fatigue during the operation process. In order to ensure the component's health, maintenance strategies are traditionally used by, reactive, preventive or proactive maintenance. Reactive maintenance involves all the corrective actions performed as a result of system failure, to restore the specified system condition as the main objective. Preventive maintenance is based on a scheduling of planned maintenance actions that aims to "prevent" commonly failures. On the other hand, proactive maintenance consists of an intended set of measures to maximize the operational availability and safety of the system. It reacts when maintenance conditions fail, but also to anticipate the non satisfaction of these conditions to avoid the failure.

Condition Based Maintenance (CBM) is characterized as a proactive maintenance strategy that uses diagnosis and prognosis to determine system's health (Luo et al., 2008). Prognosis in CBM involves prediction of system degradation based on the analysis of monitored data. Based on the current condition, its main objective is to assess, whether the process needs maintenance tasks, and if a maintenance process is needed, determining when the maintenance actions should be executed (Tran et al., 2009).

One of the enablers of CBM is the use of prognostic and health management (PHM) technologies. PHM quantifies the extent of deviation or degradation from an expected normal operating condition. It also provides data that can be used to achieve several critical goals: i.e. (1) warning of failures in advance, (2) minimizing unscheduled maintenance, extending maintenance cycles, as well as maintaining effectiveness through timely repair actions; (3) reducing the life-cycle cost of components by decreasing, inspection costs and downtime, an (4) qualification improvement, design assistance and logistical support for fielded and future systems. The strategy to perform PHM structure is based on five consecutive steps: (1) data collection, (2) degradation detection and system monitoring, (3) system diagnosis, (4) prognosis and (5) re-organization and decision stage (Zhang et al., 2009).

This present paper contributes on the "predictive" portion of PHM been the diagnosis part out of scope. Often, this prediction is characterized in the Remaining

Useful Life (RUL) estimation of components or system (Sheppard et al., 2008). Kalgren et al., (2006) proposes a grey-scale Health Index (HI), as a *continuous variable in the range from 0 to 1, to indicate component or system health/performance state from new, fully operable, undamaged condition (1.0) to complete functional failure (0.0).* The index is produced by algorithms that assess the system performance or health via measured symptoms, modeled data, and/or usage-based predictions. In our case, grey-scale HI is used to indicate the future operational capability of the system.

From engineering point of view, the deployment of the prognosis process and fault diagnosis can come from three different types of approaches; (1) Statistical approaches (Muller et al., 2008; Tran et al., 2009; Bolander et al., 2009), (2) Model-based approaches and (3) Data-driven approaches (Tran et al., 2009; Bolander et al., 2009).

The aim of the paper is to present the developed CBM architecture for on-line operation in a laboratory process. First step to solve is the system monitoring design. Then, the most significative system characteristics must be extracted for prognoses and diagnoses system health. The novelty of this work is to apply different techniques to simplify the system monitoring by using Hybrid System (HS) representation. Furthermore, an ANFIS model and HI are combined for health prediction and degradation visualization of the system.

The proposed approach is exemplified by means of an academic application, specifically a conveyor belt which moves a cart between two arm-robots.

The structure of the paper is the following. Section 2 describes the proposed CBM architecture. Section 3 outlines the model based techniques used in the paper. In Section 4, the proposed approach is applied to the conveyor belt process. Section 5 shows firsts results achieved. Finally, conclusions are provided in Section 6.

2 CBM ARCHITECTURE

Developed CBM architecture is depicted in Figure 1. This architecture includes both diagnosis and prognosis. The steps that allow inferring if the system requires some maintenance operation are:

Step1. Data collection: a real-time system is used to acquire all the available measurements.

Step2. System monitoring: A model description based on a hybrid automaton is used to follow the state of the system.

Step3. Data pre-processing: At each state, the selected system features are computed.

Step4. Prognosis: This step includes the computation of index degradation. It is computed using a HI (Kalgren et al., 2006) and an Adaptive-Network-based Fuzzy Inference System (ANFIS) for predicting the machine condition.

Step5. Supervisor: With the information provided by HI and the monitoring data from the system it will be possible to determine the maintenance tasks and, in the case of predicting a failure, it could be possible to define corrective actions.

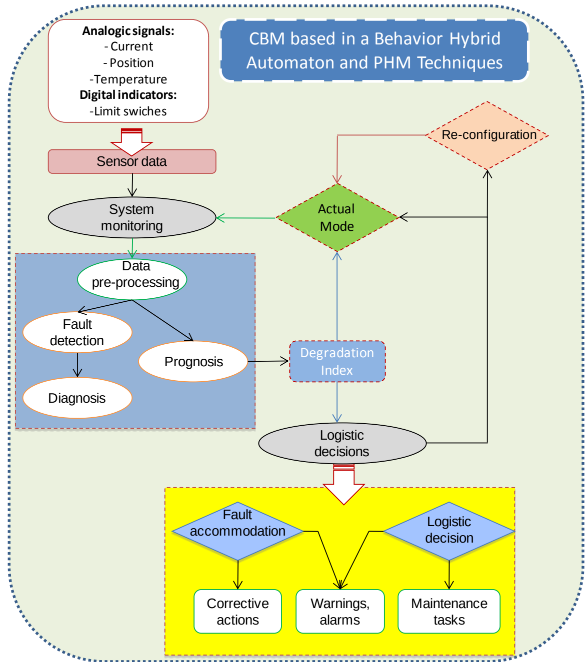
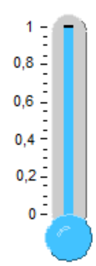


Figure 1: PHM Scheme based in hybrid system representation

The final objective is to provide information about the system operational capability to the operator, and the associated maintenance and logistics actions proposed by Kalgren et al. (2006), (see Table 1).

Table 1: Gray-Scale Health Index for CBM

	Operational Capability	Maintenance Action	Logistics Action
	Fully Functional	No Maintenance Required	No Logistic Changes
	Functional with degraded Performance	Maintenance at Convenience	Trigger Opportunistic Logistic Sparing
	Reduced Functionality	Schedule Maintenance Now	On-Demand Logistic Sparing
	Functionality Severely Impinged	Remove from Service ASAP	Logistic Emergency Sparing
	No functionality	Remove from Service Now	Logistic reflect unit out of Service

3 MODEL-BASED TECHNIQUES

Two modeling techniques are used in this approach. The hybrid system used for describing the system working stages and the hybrid approach based on ANFIS is used to predict the future system condition.

3.1 Hybrid systems

Bemporad (2006) defines a HS as a dynamic system with both continuous and discrete behaviors. As seen in Figure 2, a hybrid system can be described by a state machine representation that comes from informatics science and a continuous dynamic representation coming from control theory.

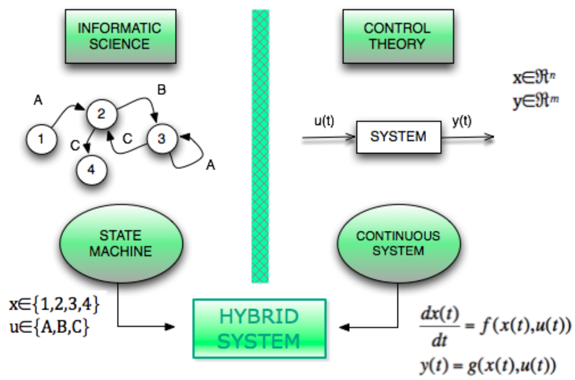


Figure 2: Hybrid system representation

Then, a hybrid system can be seen as a system which behavior is different depending on the current mode of operation among the several modes that can present. In each mode, the behavior is described by a set of difference or differential equations. The switch between different modes is controlled by 'events'. An event can be an external control signal, internal control signal or the dynamics of the system itself (Lygeros, 2004).

A hybrid automaton is a mathematical representation of a hybrid system, combining in a unique formalism, the transition of the state machine, discrete part, and differential equations to capture the continuous part (Bemporad, 2006).

A hybrid automaton H is defined as (Lygeros, 2004):

$$H = (Q, X, \sum, Init, \sum_0, T, C) \qquad (1)$$

with:

- $Q = \{q_1 \cdots q_n\}$ is finite set of discrete states or modes where each state represents a functional system model.
- $X = \Re^n$ is set of continuous variables.
- $\sum$ is the set of events corresponding to control the switches between modes or fault events.
- $Init$ is the set of initial conditions, $Init = \{x_0, q_0\}$
- $\sum_0 \subseteq \sum$ is the set of observable events.
- T is the transition function, $Q \times \sum \to \sum$.
- C is guard condition

And, the discrete dynamic part of the system is represented by the system mode: $M = (Q, \sum, q_0, T)$ (Bayoudh et al., 2006).

The approach relies on evaluating the system degradation exhibited at the continuous level into hybrid automaton. A full process includes a normal or degraded system mode characterized by X.

A behavior automaton for each system mode - normal or degraded - is defined by Bayoudh (2006), as:

$$M^i_{behav} = \left(Q^i_{behav}, \Sigma^i_{behav}, q^i_{behav}, T^i_{behav}\right) \qquad (2)$$

where, Q^i_{behav} is the set of behavior automaton states, each state is characterized by a different working mode, and $\Sigma^i_{behav} \subseteq \Sigma_{behav}$ is the set of events.

3.2 ANFIS as a time series prediction

ANFIS architecture is composed of fuzzy sets (FIS) with Takagi-Sugeno rules, allowing the introduction of the expert knowledge, and a neural net (NN) capable to learn from data. Figure 3 presents ANFIS classic architecture for two variables *x* and *y* where the *x* domain is covered by the fuzzy sets *A1* and *A2*, and the *y* domain by *B1* and *B2*. Each domain can be described as a fuzzy set.

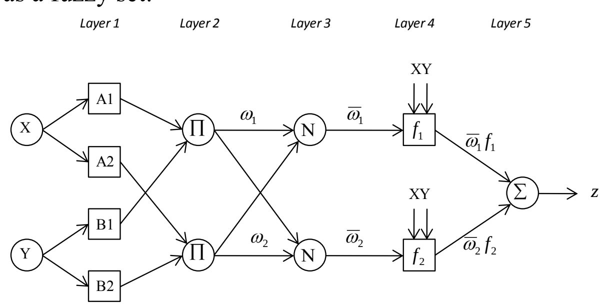


Figure 3: ANFIS structure

In a fuzzy set, *S* is a function that links every element of the domain, *D*, with a point in the constant interval [0,1]. Zero is used to indicate that the element is not a member of *S*, and one indicates the complete membership of the element to *S*. The values between 0 and 1 represent the partial degrees of belonging to the interval (Velásquez et al., 2004).

The function that links every element of the domain *D* in the interval [0, 1] is the membership function, $\mu_M(x)$, and it can be represented using different mathematical functions. The one used in this work, is the sigmoid-*S* function:

$$\mu_M(u; \gamma, c) = \frac{1}{1 + \exp[-\gamma(u - c)]} \qquad (3)$$

where $\{\gamma, c\}$ are the modifiable parameters governing the shape of the membership function.

In ANFIS *layer 1* (Figure 3), the (*x, y*) input for a process implies: first, to calculate $\mu_{A1}(x)$, $\mu_{A2}(x)$, $\mu_{B1}(y)$, $\mu_{B2}(y)$ using Eq. (3) having the membership input to the fuzzy set. Then, the membership computation data flows to *layer 2* where the product inference for every rule $\omega_j = \mu_A(x) \cdot \mu_B(y)$ satisfying the Takagi-Sugeno rules are computed (Velásquez et al., 2004).;

$$\begin{aligned} &if\ x \in A_1 \wedge\ y\ \in\ B_1 \Rightarrow z = p_1x + q_1y + r_1 \\ &if\ x \in A_2 \wedge\ y\ \in\ B_2 \Rightarrow z = p_2x + q_2y + r_2 \end{aligned} \qquad (4)$$

In *layer 3,* this data flows through the NN part of ANFIS scheme and establishes the contribution percentage of each rule to the final solution $\overline{\omega_j} = \frac{\omega_j}{\sum_{i=1}^{N}\omega_i}$; *Layer 4* computes the product of normalized values achieved in *layer 3*, like $\overline{\omega_i}f_i$; and finally in *layer 5*, the output is calculate as $\sum_i \overline{\omega_i}\, f_i$ (Velásquez et al., 2004).

To determine the ANFIS input as a time series prediction the past process values up to sample *'k'* are used to predict the value at some point in the future ' $k + n$ '. The standard method for this type of prediction is to create a mapping from m points of the series spaced by λ samples as follows:

$$\mathbf{x}(k+n) = [[x(k-(m-1)\lambda], \ldots x(k-\lambda), x(k)] \qquad (5)$$

where $\mathbf{x}(k+n)$ is the predicted value.

4 PROPOSED APPROACH

Our CBM approach uses a behavior automaton to characterize the real system performance. In each working mode, continuous variables are used to compute some characteristics parameters that are send to ANFIS network. The ANFIS network using those characteristic parameters determines the system condition index that will allows the health system prediction in the future n cycles. This allows characterizing the system degradation to facilitate logistic support decisions. A conveyor belt, which moves a cart between two arm-robots, is used to illustrate this approach.

4.1 System description

The conveyor belt (Figure 4) uses an AC electrical motor to move the belt from one robot-arm to another. A frequency variator with a two channels encoder is used to control the motor velocity. The process starts with the cart in front of robot A, with the conveyor stopped -motor off- and the cart locked. When robot-arm A finishes it work, the first task is to un-lock the cart and then the conveyor belt movement starts, moving the cart to robot-arm B. After, robot-arm B starts their job. When it finishes, the conveyor belt returns the cart to the initial position, and the job starts again. The velocity set-point is composed of an acceleration ramp, a constant value and deceleration ramp.

To monitor the motor behavior a temperature sensor (T_M) and a current sensor of the AC motor (I_M) are used. The control system also provides the following digital information:

- σ_{cb}: cart locked
- σ_{aAB}: finishing acceleration ramp from A to B
- σ_{dAB}: starting deceleration ramp from A to B
- σ_{aBA}: finishing acceleration ramp from B to A
- σ_{pA}: cart is in front of robot-arm A
- σ_{pB}: cart is in front of robot-arm B
- σ_A: finishing job of Robot-arm A
- σ_B: finishing job of robot-arm B

Different periods of σ_A and σ_B have been considered.

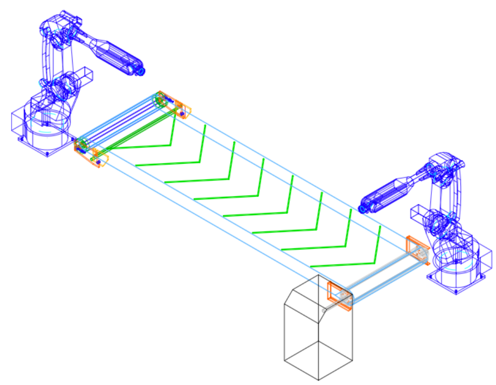


Figure 4: Proposed application

4.2 Behavior Hybrid Automaton Representation for system monitoring

A conveyor belt system can be modeled through a behavior automaton representation as in Eq. (1) where the set of observable events are:

$\Sigma_0 = \{\sigma_{cb}, \sigma_{aAB}, \sigma_{dAB}, \sigma_{aBA}, \sigma_{pA}, \sigma_{pB}, \sigma_A, \sigma_B\}$;

and, the set of continuous variables are $X = \{T_M, I_M, P, V\}$, being P and V the cart position and velocity computed using the encoder signal.

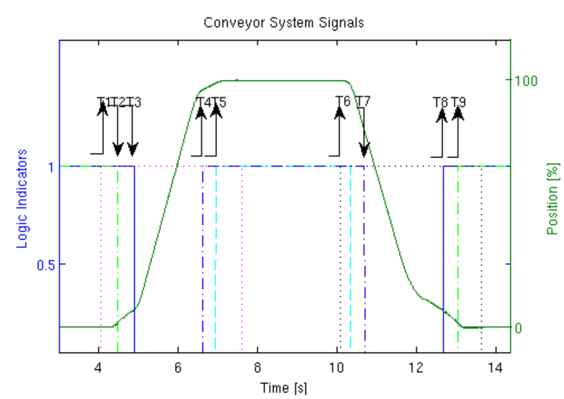


Figure 5: Conveyor system signals

The cart position is used to define the set of normal working stages. In this case study 9 states have been identified. Figure 5 shows in solid green line the cart position versus time, $P(t)$, where 0% and 100 % correspond to σ_{pA} and σ_{pB}, respectively; and, the step signals[2] and the set of transitions, T[3]. Table 2 and 3 describe the set of normal states, Q, and the relation between T and $\sum_0$. Figure 6 shows the structure of the hybrid automata proposed.

In this paper only the states $q4$ and $q8$, are used to extract the motor characteristics. These states allow to identify the area where the conveyor belt is working with constant velocity. In these stages some dynamic characteristic can be extracted, e.g. velocity (the derivative of the position), current amplitude and frequency of the AC motor and its temperature.

Table 2: States description, Q

STATES	DESCRIPTION
q1	Cart in robot A
q2	Un-locking the cart
q3	Conveyor belt acceleration from A to B
q4	Constant speed, from A to B
q5	Conveyor belt decelerations, from A to B
q6	Cart in robot B
q7	Conveyor belt acceleration from B to A
q8	Cart travelling, from B to A
q9	Locking the cart

Table 3: Transition description

TRANSITIONS	DESCRIPTION
t1 (magenta dotted line)	$\sigma_A = \uparrow$
t2 (green dash-dotted lines)	$\sigma_{cb} = \downarrow$
t3 (solid blue line)	$\sigma_{aAB} = \uparrow$
t4 (dashed blue line)	$\sigma_{dAB} = \uparrow$
t5 (dash-dotted cyan line)	$\sigma_{pB} = \uparrow$
t6 (dotted black line)	$\sigma_B = \uparrow$
t7 (dashed blue line)	$\sigma_{aBA} = \uparrow$
t8 (blue solid line)	$\sigma_{pA} = \uparrow$
t9 (green dash-dotted line)	$\sigma_{cb} = \uparrow$

4.3 Prognostic calculations and health index

After system monitoring developed, the prognostic part of PHM scheme, to predict the plant health, should be implemented. ANFIS is used for a gray-scale health index computation.

According to ANFIS structure (Figure 3), to train ANFIS model the input and output variables must be provided. For conveyor belt application 8 inputs are used: $\{\overline{V^1}, \overline{T^1}, \overline{A_I^1}, \overline{f_I^1}, \overline{V^2}, \overline{T^2}, \overline{A_I^2}, \overline{f_I^2}\}$, where super indices 1 and 2 denote the values computed in the states $q4$ and $q8$, respectively. In each working cycle the mean value of: velocity ($\overline{V}$), temperature ($\overline{T}$), and current amplitude ($\overline{A_I}$) and frequency ($\overline{f_I}$) provided by I_M are computed.

Five fuzzy sets for each variable are defined, characterizing the five degradation modes proposed in gray-scale HI.

The output fuzzy sets are codified to produce the system condition (*SC*) number, allowing to visualize the system degradation. The *SC* indicates the mode in which the plant will be after *n* cycles. Mode 1 means that the system will be fully functional while mode 5 will not be functional at all. Table 1 shows the ANFIS output.

Matlab's Fuzzy logic toolbox is used for the entire process of training and evaluating the neuro-fuzzy model. ANFIS is used applying Eq. (5), with m = 4, λ=50 and n=50, to forecast 50 signal cycles ahead.

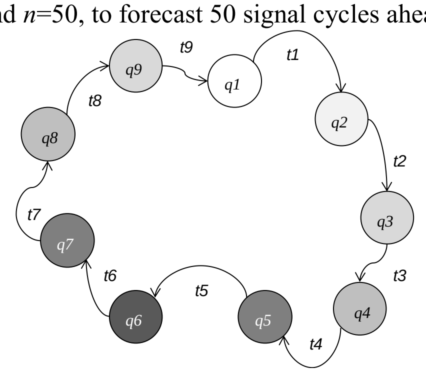


Figure 6: Conveyor belt states and transitions to monitor the system

4.4 Motivational Example

To illustrate how the proposed fusion of ANFIS approach for predicting the evolution of the system heath and the use of gray-scale HI a motivational example is proposed that considers only two signals $\{\overline{f_I^1}, \overline{T^1}\}$, hence *x* and *y*.

ANFIS approach, recalled in Section 2.2, with *x* and *y* as a system signals, and the domains A and B, is used to forecast signals behaviors.

In Figure 7, *x* and *y* are represented into two *y-axes* where in the lefth axes apears the HI while in right axes the real signal value along working cycles are presented, respectively. The degradation index follows the process signals characteristics and indicates the health or performance state from normal with a 1 to complete damage with a 0. Then, there signal can be

[2] The relation between step signals and transitions are described in Table 2.

[3] ↑ and ↓ means OFF-ON and ON-OFF signal activation, respectively.

descomposed in subsets equivalent to each HI stage (Table 1) being each membership functions presented in Eq. (3).

To obtain an indicator that presents the total system damage, the following levels are used: A: {*A1- Fully functionality, A2- Functional with degraded performance, A3- Reduced functionality, A4- Functionality severely impinged, A5- No functionality* } and the same classification for fuzzy sets B are obtained. Moreover, the fuzzy rules express the full system degradation in *n* cycles:

$$\begin{gathered} if\ x \in A_1 \wedge\ y\ \in\ B_1 \Rightarrow z = fully\ functionality \\ if\ x \in A_2 \wedge\ y\ \in\ B_2 \Rightarrow z = functionality\ degraded \\ if\ x \in A_3 \wedge\ y\ \in\ B_3 \Rightarrow z = reduced\ functionality \\ if\ x \in A_4 \wedge\ y\ \in\ B_4 \Rightarrow z = impigned\ functionality \\ if\ x \in A_5 \wedge\ y\ \in\ B_5 \Rightarrow z = no\ functionality \end{gathered}$$

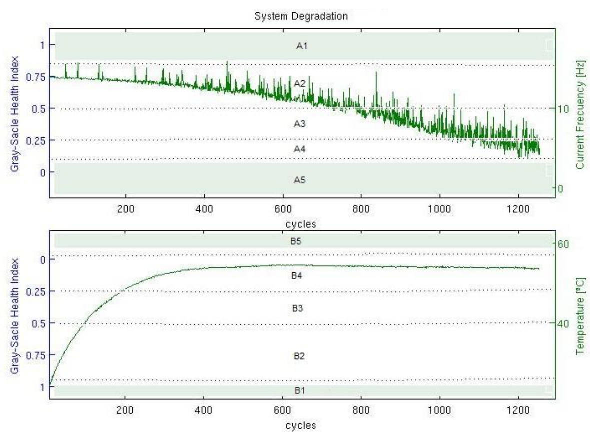


Figure 7: Grey-Scale Health Index example of mapping.

5 FIRST RESULTS

In this section two scenarios illustrate the proposed methodology. Each scenario is characterized by the number of working cycles (*WC*) and the remaining time in $q1$ and $q6$, (RT_{q1}) and (RT_{q6}), respectively. The operation conditions for each scenario are described in Table 4. Both scenarios correspond with a degraded behavior (dB). To generate these scenarios different levels of friction are introduced in one roller belt causing the system malfunction.

Table 4: Scenarios description

SCENARIO	*WC* (number)	RT_{q1} (sec)	RT_{q6} (sec)	Behavior
Scenario 1	300	5	10	dB
Scenario 2	550	5	5	dB

The system monitoring signals appears in Figure 8: $\bar{V}$, $\bar{T}$, $\overline{A_I}$ and $\overline{f_I}$, for each scenario on either conveyor belt directions, from robot-arm A to B and B to A. The degraded behavior is reflected in velocity and current frequency, both variables being significatively decreased. Otherwise, in the two scenarios, temperature increases fast at the beginning and, after a transition, it keeps constant. These eight inputs are introduced to the ANFIS model to forecast the full system condition.

The obtained results are shown in Figure 9 where ANFIS model output, *SC*, is presented for both scenarios. *SC* appears in a solid blue line and the desired output behavior in red dash-dotted line. *Y-axes* shows the *SC* mode from 1 fully functionality to 5 no functionality, and *x-axes* presents the cycle prediction number.

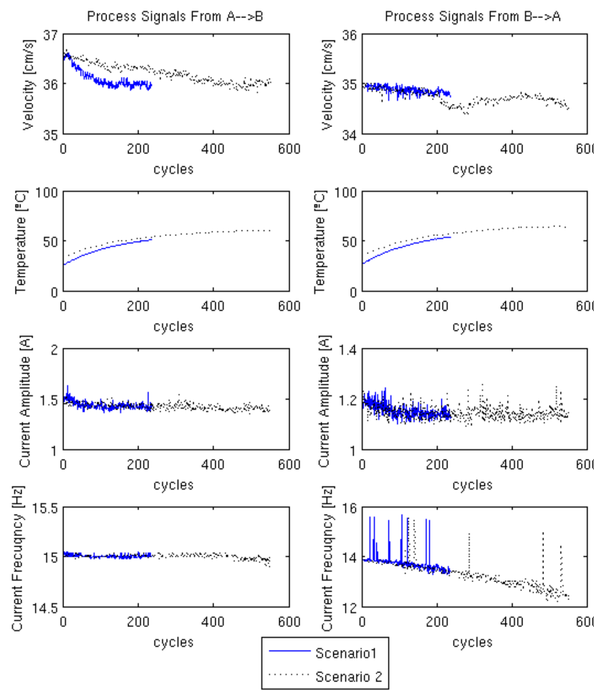


Figure 8: Conveyor belt motor characteristics

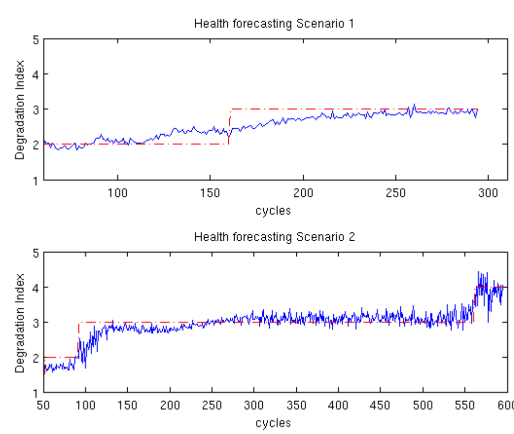


Figure 9: Health Prediction

6 CONCLUSION

This work is a starting point to show how a system representation based on a hybrid automaton has potential benefits for extracting the most specific system parameters. The proposed approach permits system monitoring for the application of prognostic and diagnosis methodologies to monitor the system condition, facilitating the visualization of degradation system as well as maintenance and logistic task scheduling.

The hybrid model representation enables in an easy way the introduction of PHM techniques to system monitoring. The use of ANFIS and the gray-scale HI has allowed to predict the future condition of the conveyor system in a single formalism, the System Condition *SC* number.

The combination of hybrid methodology and PHM techniques has produced positive results and has facilitated issues related with condition-based maintenance and tolerant control methodologies. As a consequence, this research could be pursued in the future, working in the prediction information and *SC* to build a degradation automaton making possible to manage logistic and maintenance tasks for condition based maintenance.

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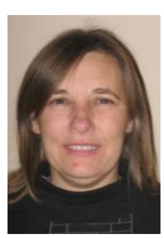

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