SEMI-QUALITATIVE TEMPORAL EPISODES PROGNOSIS FOR PROCESS SUPERVISION.

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Abstract– This paper deals with a prognosis method that is used in an operation support system. The role of prognosis in a supervisory system is analysed. Then, a supervision method based on trend analysis is explained. First the on line extraction of semi-qualitative episodes from a noisy signal is described. The method uses a segmentation algorithm, a classification of the segments into seven temporal shapes and a temporal aggregation of episodes. Discontinuities are preserved, which is important in case of failure. Then, the estimation of relevant variables future evolution is described, which is based on the last semi-qualitative episode. A two tanks system is used as a pedagogical example to illustrate the method potential. An industrial application is then described shortly.

Keywords – Supervision, Prognosis, Condition based maintenance, Trend extraction, Qualitative Analysis.

1. INTRODUCTION

Process technology has changed to more complex plants with a high degree of automation. This has enhanced the quality and efficiency of normal operation, but has also made systems more vulnerable to faults. As a consequence, industrial attention has moved towards increased dependability of systems (Blanke *et al.*, 2003).

Dependability is synonym of high degree of availability, reliability and safety. These three features indicate how a component failure impacts on the production, on the process and on the environment. A component failure can be defined as the inability of the component to perform a function; this failure may cause a set of faults in the system, meaning that some characteristic property or variable of the system departs from an acceptable range (Venkatasubramanian, 2001). For human operators or for automatic supervisory systems, detecting faults is done by means of symptoms, based on changes of observable variables from normal behavior.

In order to maintain process dependability, a modern Operation and Management (O&MM) system must help the operators making quick decisions about the control of abnormal process situation, the start up and shut down of process or sub-systems, or performing a reconfiguration or accommodation of the process based on fault-tolerant control (FTC) strategies. Moreover, the O&MM system must help the operator making decisions about the maintenance policy of the different equipments. The most recent computer aided maintenance systems are based on the concepts of Condition Based Maintenance (CBM): the replacement or reparation of components should be based on the real state of the component rather than on an a priori planned procedure.

Therefore, a complete O&MM system comprises a number of different functional capabilities such as data acquisition, signal processing, diagnosis, prognosis, and decision making. The main purpose of prognosis is to anticipate and prevent critical failures.

Prognostic results are used for proactive decisions about preventive actions with the economic goal of maximizing the service life of replaceable components, while minimizing operational risks (Mathur *et al.*, 2001). In CBM, the prognosticator plays the role of linking the diagnostic information to the maintenance scheduler system. The prognosticator is viewed as a predictor which receives fault data from the diagnostic module, and determines the allowable time window during which machine maintenance must be performed, so that the integrity of the process may be kept as high as possible. Algorithmically, the prognosticator is viewed as a dynamic time series predictor, whose goal is to predict the future values of a variable, using past values. The term "dynamic" refers to the functional requirement that the target output is dynamically updated, as more information becomes available from the diagnostic system. Prediction of the course in which a fault could develop can be looked at from two different viewpoints: one is to identify the fault value at a certain time moment and the other is to find the time moment when the fault reaches a given value. The first viewpoint is more related to the prediction of critical variables or symptom values. The second viewpoint is more associated with the prediction of the time to failure or the remaining useful lifetime of a component. Prognosis has been the Achilles' heel of the CBM system with its inherent challenges in efficiently representing and managing uncertainty and accounting for extreme operating modes (Vachtsevanos *et al.*, 2000).

Numerous approaches to prognosis exist, which range from simple historical failure rate models, which are very weak, to high-fidelity physical models, very costly to obtain (Propes *et al.* 2002). Many works report Artificial Neural Networks (ANN) as an intermediary solution for prediction (Khiripet and Vachtsevanos, 2001). However the ANN training period makes them prohibitive for some applications. This is particularly true for the description of fault or failure behaviour that can hardly be known exhaustively in advance. This is the reason why using semi-qualitative trends is proposed in this paper.

Trend analysis extracts information from numerical data and represents it symbolically. A qualitative temporal trend is a qualitative history that is represented by a sequence of consecutive and non overlapping episodes. The description uses a small set of symbols called *primitives*. An *episode* corresponds to a time interval of uniform behaviour, when relevant qualitative properties of a signal are constant and is generally described as {*primitive*, *temporal extension*}. Trend analysis has been proposed by several authors for process supervision (Rengaswamy and Ventaakasubramanian, 1995; Colomer J. *et al.*, 2002). In this case, the primitives should be easily interpreted by the operators.

In this paper, trends of variables that have been detected as suspect by a diagnostic system are extracted on line. As an episode represents only the relevant behaviour of the signal over a time window that is determined on line, in function of the signal dynamics, the proposal is to extrapolate the last episode in order to provide the operator with an idea about how the variable will behave in the future. In section two, the algorithm used for trend extraction is detailed. In section three, the use of trend analysis for variable prognosis is explained; a pedagogical example is used for explanatory purposes. An industrial example is also described shortly.

2. TREND ANALYSIS BASED PREDICTION

This paragraph presents a methodology that has been developed to extract on-line episodes from a time series and to aggregate them into a semi-qualitative trend (Charbonnier *et al.*, 2002, 2004). The use of a semi-qualitative trend is preferred to a purely qualitative one to allow representing quite precisely numerical data. The proposed trend extraction method consists in four steps detailed in the following sections.

1.1. On line signal segmentation of rough data into linear segments

Data are described by successive linear segments. The segmentation algorithm determines on line the moment when the current linear approximation is no longer acceptable and when a new segment should be computed. Outliers are previously filtered by the algorithm. Two consecutive segments may be discontinuous. Each segment is based on a linear model:

$$y(t) = p * (t - t_o) + y_o \qquad (1)$$

where t_o is the time when the segment begins, p is its slope and y_o is the amplitude at time t_o. Parameters y_o and p are identified using a least squares criterion.
The technique used to determine t_0 is the cumulative sum (*cusum*). This technique is very sensitive to signal changes.

$$cusum(t_1 + k\Delta t) = \sum_{j=0}^{k} e(t_1 + j\Delta t) \qquad (2)$$

where $e(t_1 + j\Delta t) = y(t_1 + j\Delta t) - \hat{y}(t_1 + j\Delta t)$ is the difference between the measurement y and the linear extrapolation $\hat{y}$.

The decision at time $t_1 + k\Delta t$ is made with predefined thresholds:

- If $\left|cusum(t_1 + k\Delta t)\right| \le th1$: current model acceptable.
- If $\left|cusum(t_1 + k\Delta t)\right| > th1$: $y(t_1 + k\Delta t)$ and t_1 are memorized.
- If $\left|cusum(t_1 + k\Delta t)\right| \ge th2$: current model no longer acceptable. A new linear approximation is computed using the memorized data and the *cusum* (2) is reset to 0 (Figure 1).

The segment i ends at time $t_e(i)$, one sampling time before the next one starts. The ordinate at time $t_e(i)$, $y_e(i)$, is calculated using Ts as the sampling period:

$$t_e(i) = t_o(i+1) - Ts \tag{3}$$

$$y_e(i)=p(i).[t_e(i)-t_o(i)]+y_o(i) \tag{4}$$

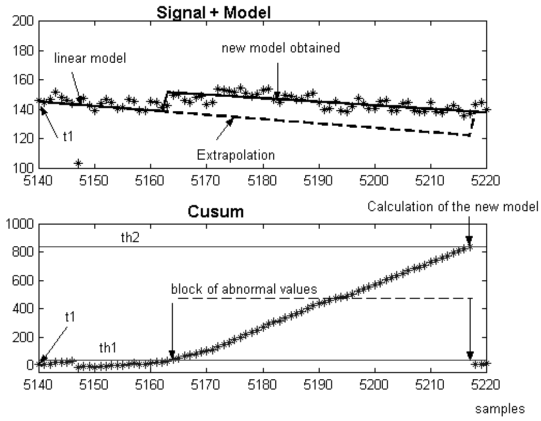

Figure 1. Segmentation

1.2. Classification of two consecutive segments into 7 possible temporal shapes.

The new segment is used with the preceding one to form a shape. Seven temporal primitives are used for this classification: *Increasing, Decreasing, Steady, Positive Step, Negative Step, Increasing/Decreasing Transient, Decreasing/Increasing Transient.*

A shape is described by three features (Figure 2):

- I: the total variation produced by the shape:

$$I(i) = y_e(i) - y_b(i) \tag{5}$$

- I_d: the variation due to a discontinuity between two segments:

$$I_d(i) = y_o(i) - y_b(i) \tag{6}$$

- I_s = the variation due to the slope of the new segment:

$$I_s(i) = y_e(i) - y_o(i) \tag{7}$$

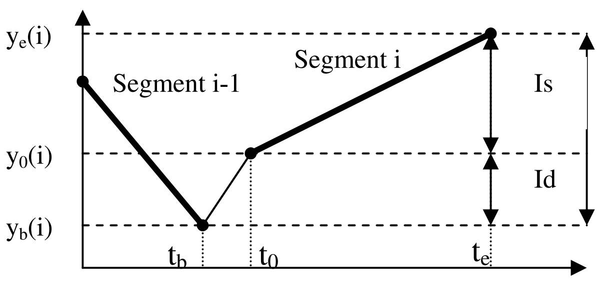

Figure 2. Shape formed with segments i and i-1.

The shape associated with the segment i starts at the end of the previous segment:

$$t_b(i) = t_e(i-1) = t_o(i) - Ts \tag{8}$$

Once the different features have been computed, a classification is performed using one predefined threshold t_{hc} and the following rules:

If $|I_d| \geq t_{hc}$ the shape is *Discontinuous* {It is a *Step* or a *Transient}* **Else** the shape is *Continuous* {It is *Steady*, *Increasing* or *Decreasing}.*

If the shape is *Continuous* **AND** $|I| \leq t_{hc}$, then the shape is *Steady* **Else**, it is *Increasing* or *Decreasing,* depending on the sign of I.

If the shape is *Discontinuous* **AND** $|I_s| < t_{hc}$ **Then** the shape is a *Step,* positive or negative depending on the sign of *Id* **Else If** $sign(Id) \neq sign(Is)$ it is *Transient* **Or If** $sign(Id) = sign(Is)$ it is *Increasing or Decreasing.*

If the shape is *Transient*, it is *Decreasing/Increasing* or *Increasing/Decreasing*, depending on the signs of *Id* and *Is*.

The classification of the segment into a temporal shape is thus easily obtained with only one parameter t_{hc} and provides symbolic information meaningful to the operator.

1.3. Transformation of shapes into semi-quantitative episodes using three primitives {Steady, Increasing, Decreasing}.

Quantitative information, generated by the data segmentation, can be associated with qualitative information generated by the classification, in order to produce semi-quantitative episodes. A semi-quantitative episode is described by:

$$[Primitive,\ t_b(i),\ y_b(i),\ t_e(i), y_e(i)] \tag{9}$$

To obtain an easily understandable trend, only three basic primitives are used for the episodes: {*Steady, Increasing, Decreasing*}.

If a shape is in {*Steady, Increasing, Decreasing*}, the symbolic information is obviously converted into one of the symbolic primitives. The corresponding semi-quantitative episode is for instance:

$$[Steady,\ t_e(i-1),\ y_e(i-1),\ t_e(i),\ y_e(i)] \tag{10}$$

If the shape is a *Step* or a *Transient*, it is split into two parts, each being associated with one of the proposed primitives. A *Positive Step* (respectively *Negative*) described by the shape [P*ositive-Step*] and the two segments *(i-1)* and *(i)*:

[t_0(i-1), y_0(i-1), t_e(i-1), y_e(i-1)]; [t_0(i), y_0(i), t_e(i-1), y_e(i)]

becomes:

[*Increasing* (respectively *Decreasing*), *t_e(i-1), y_e(i-1),t_0(i), y_0(i)*] + [*Steady, t_0(i), y_0(i), t_e(i), y_e(i)*].

1.4. Aggregation of the current episode with the previous ones to form a concise history

The aggregation of episodes consists in associating the most recent episode with the former ones to form the longest possible episode. The possible aggregations between two episodes are:

- *Increasing* + *Increasing* = *Increasing*
- *Decreasing* + *Decreasing* =*Decreasing*
- *Steady* + *Steady* = *Steady* if the increase of the global sequence *[ye(i)-yb(i-1)]<t_{hc}*,
- *Steady* + *Steady* = *Increasing* (or *Decreasing)* if the increase of the global sequence *[ye(i)-yb(i-1)]> t_{hc}* (or *[ye(i)-yb(i-1)]<t_{hc})*.

t_{hc} is the threshold used to separate the shapes *Steady* and *Increasing*. This allows the detection of slow drifts in the signal. The drift will take more time to be detected since it requires the association of at least two steady trend patterns. However, this is not a major drawback since the appearance of a slow drift does not represent an immediate danger for the plant.

The aggregation algorithm follows the next rules:

If the previous episode is *[Increasing, t_b(i-1), y_b(i-1), t_e(i-1), y_e(i-1)]* **And** the next episode is *[Increasing, t_b(i), y_b(i), t_e(i), y_e(i)]* **Then** the new episode is *[Increasing, t_b(i-1), y_b(i-1), t_e(i), y_e(i)]*.

If the next episode is *Steady* (or *Decreasing*) **Then** it cannot be aggregated and a new episode is generated *[Increasing, t_b(i-1), y_b(i-1), t_e(i-1),y_e(i-1)]; [Steady* (or *Deacreasing*), *t_b(i), y_b(i), t_e(i), y_e(i)]*.

1.5. On-line implementation of the methodology

At time *tc*, the current time, when a new linear approximation has just been calculated by the segmentation algorithm, the previous segment is thus completely defined by:

$$\text{Seg-i-1: } \{t_0(i-1), y_0(i-1), t_e(i-1), y_e(i-1)\} \quad (11)$$

The steps - classification, transformation into semi-quantitative episodes, aggregation – are achieved at first using the previous segment *(i-1)*. The definitive trend is then extracted until *t_e(i-1)*.

To extract the trend until the current time *tc*, the current segment is temporary defined by:

$$\text{Cur-Seg: } \{t_0(i), y_0(i), tc, y_e(i)\} \quad (12)$$

with:

$$y_e(i)=p(i).[t_c-t_o(i)]+y_o(i). \quad (13)$$

The steps — classification, transformation into semi-quantitative episodes, aggregation — are then achieved using the current segment *(i)* to extract a temporary trend. Later, when a new linear approximation will have been calculated, the current segment will become the previous segment and will now be completely defined. It will be aggregated with the definitive trend and a temporary trend will be calculated using the new current segment.

3. TREND ANALYSIS FOR PROGNOSIS

For process supervision and operator support, trend analysis results can be used in different ways to inform the operator about the future behaviour of a given signal. The qualitative information such as variable is *Steady* or *Increasing* is by itself a useful tool to assist the operator in its decision. Moreover, the semi-quantitative episodes can be used to predict the value of the monitored variables in a time window. The segmentation algorithm provides the linear model that better describes the behaviour of the signal. If an alarm threshold had been chosen, then the model $y(t)=p(t-t_o)+y_o$ could be used to solve the inverse problem: how much time is needed for the signal to arrive to this threshold y_{th}?

In this section a two tanks system is used to illustrate the method (Figure 3). The system has been modelled using physical relations and the model has been implemented with Simulink. The simulator allows the simulation in normal condition as well as in faulty situations. Noise is added to simulated variables. The lower tank level is controlled by the servo-valve *Vk1*. Measurements available to the control and supervision systems are the water levels *h1*, *h2* and output flow of each tank *q1*, *q2*. Different kinds of fault scenario are considered in the following paragraphs.

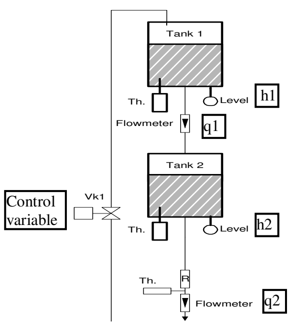

Figure 3. The 2 tanks system.

1 Gradual leakage in tank 1

The scenario described in Figure 4 (and subsequent ones) starts with an *h2* level set-point change at time 0, followed by a failure at time 6000 sec. A ramp leakage is introduced in tank 1, simulating a progressive failure. The control system compensates the leakage, maintaining the tank levels equal to their reference values by increasing the valve opening. The operator can see on the interface the variables trends and their prediction (grey background).

The predicted value of each variable is represented on the right side of each curve. This prediction is based on the last episode, which is extrapolated on a long time horizon. The prediction allows seeing level *h1* remaining constant for a long time thanks to the regulation loop; but this will no longer be the case when the valve reaches its saturation level (100%). The operator has an idea about the time left before this saturation and can thus perform a counteraction (a reduction of the set point value for level *h2*, or a programmed shutdown, or a call to the maintenance service).

2 Abrupt leakage in tank 1

In this scenario (Figure 5), a step leakage is introduced in tank 1, simulating an abrupt failure. Since the failure is not very large, the control system compensates the leakage by increasing the valve opening. The operator can see that this situation could be maintained until the next maintenance period or plan a maintenance policy.

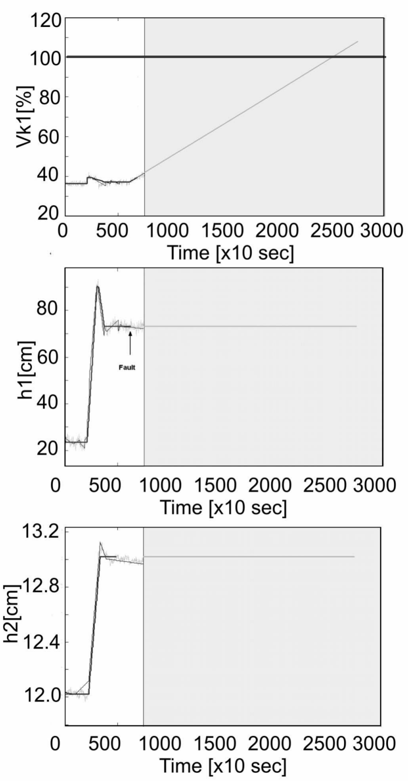

Figure 4. Gradual leakage, *Vk1, h1, h2*.

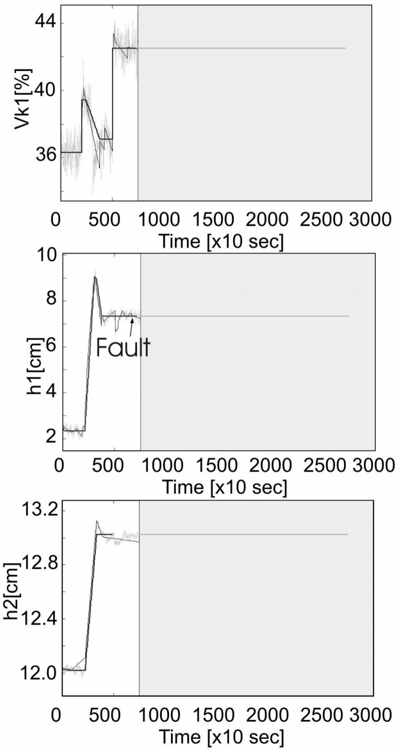

Figure 5. Abrupt leakage, Vk1, h1, h2.

3 Industrial example

The method has been applied to data corresponding to experiments made on a hydraulic looper, by SMS-DEMAG. The looper is part of a hot rolling mill and designed to eliminate the mass flow disturbances during the rolling process, maintaining a constant strip tension. The control consists in a position control with an internal force control loop. Figure 6 superimposes the results of tests practiced several times each day during 4 months (position and force with respect to time; position wrt force, used to analyze backlash). The peaks observed in the force and hysteresis curves correspond to a process fault. Figure 7 shows the compact history corresponding to the deadband width in the backlash curve. Very few segments (11) are needed to describe the data, corresponding to 500 records. The clear discontinuity allows the operator to determine easily in which period the fault was disturbing the process functioning. It can be seen also that at the present time (500), the process is normal and the extrapolated behavior does not show any suspect state.

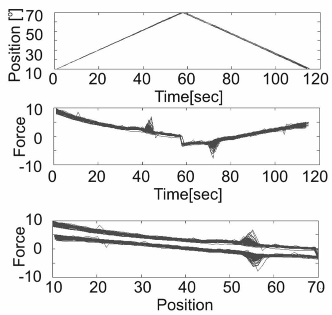

Figure 6. Hydraulic looper data (4 months)

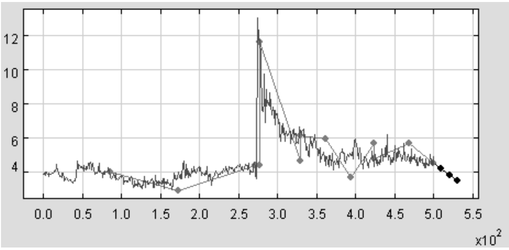

Figure 7. Trend extraction for the backlash signal.

4. DISCUSSION

This paper is focused to prognosis as part of a decision support system for abnormal situation management. The prognosis is based on trend analysis. Trends constitute a powerful and concise representation of signal relevant changes. As shown with a pedagogical example, trends can be used in supervision support systems for the prediction of critical variables. The operator is then capable of reasoning whether the fault could be tolerated during a given period until the next maintenance period or whether it must be compensated quickly. The signal trend (abrupt changes, succession of *Increasing/Decreasing* episodes etc.) can be further interpreted and related to fault isolation if the operators have a good experience of fault management.

The algorithm low computational complexity allows its use on-line. Three thresholds are needed for data segmentation and classification. They depend on the noise level and signal variation rate and are chosen in function of a priori knowledge of the variable behavior in normal operation. *th1* is a threshold that is easily tuned taking into account the noise corrupting the variable (for instance equal to the standard deviation). *th2* is tuned as a function of the delay required to detect a variable change. *th2* corresponds to the integral of the change to be detected on a time interval equal to the delay necessary to detect this change. *th2* can be tuned depending on the kind of transients that should be detected (duration D and amplitude A). Indeed, any transient which integral value (DxA if the transient is a step) is smaller than *th2* will be filtered by the segmentation algorithm. A change in these thresholds value does not significantly change the episodes extracted but may change their beginning or end time, if the data are very noisy. *thc* must be tuned to permit detection of variable significant changes. If it is too low compared to the noise level, false episodes (succession of increasing-decreasing) may be extracted. In this case, the prognosis may be misleading, thus it is better to overestimate *thc.*

The proposed trend extraction relevance lies in its capability to take quickly into account important signal modifications (which are of major importance when an abrupt fault is occurring), while filtering minor modifications. The characteristic of the proposed method, compared to other methods in the literature, relies in its robustness to noise: it does not use the signal derivative estimation to make decision.

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