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CONDITION BASED MAINTENANCE FOR ROBOT ACTUATORS

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Abstract : Condition Based Maintenance (CBM) enables the preemptive maintenance of systems that are subject to incipient faults and is, therefore, an indispensable attribute of robot actuator intelligence. This paper present aspects of a Decision Making (DM) method which facilitate actuator condition based maintenance and is called DM/CBM. Achieving effective maintenance could be of benefit to companies, which can increase profit by the reduction of maintenance costs, as well as to customers who can enjoy improvement of service quality.

1. INTRODUCTION

Legacy condition monitoring methods are founded on the premise that a fault is any significant deviation from nominal system behavior. Consequently, legacy systems are often to blame for “false alarms” that arise from system changes that are significant, but do not compromise the system’s ability to meet its task demands. DM/CBM is predicated on the concept of a functional fault—system degradation that endangers current or projected future task execution. In order to do this, DM/CBM utilizes performance envelopes to characterize both actuator capabilities and actuator task demands. An underlying sensor based model of the actuator is used to continuously update the actuator performance envelope, which is compared with the task envelope to provide a means for detecting performance-compromising faults. Once refined and tested, DM/CBM may be integrated into an embedded software framework known as AMOS (Actuator Management Operational Software) as a key contribution to further enhance the actuator’s intelligence.

The standardized actuators are the fundamental building block for modular robots, aircraft, submarines, and general industrial automation [10]. Demand for enhanced reliability and cost-effectiveness of standardized actuator modules utilized in open architecture intelligent systems calls for the implementation of distributed Condition Based Maintenance techniques [10]. CBM is a supervisory control algorithm that is solely dedicated to monitoring machine systems or processes in order to detect and diagnose incipient faults at an early stage. By providing an early warning of potential failures, preemptive maintenance may be carried out rather than reactive maintenance [4]. The underlying principle upon which CBM operates is that machines provide advanced warning of failure through symptomatic performance degradation. By detecting and identifying these symptoms early in their onset, maintenance may be carried out before system safety and availability are compromised. Since CBM is concerned with faults that develop slowly over time, we restrict our attention mostly to incipient faults.

When system engineers set out to design a robot, they typically use as many off-the-shelf components as possible. When selecting actuators, they first formulate the performance specifications that the task requires, and then they search through manufacturer specifications to find an actuator that meets or exceeds the required performance specs. DM/CBM uses a similar logic, but instead of deciding which actuator to buy, the decision is whether or not to replace a degraded actuator with a healthy one based on its assessed condition. It is hypothesized that this method of condition assessment and fault related decision-making will not only provide a quantitative estimate for the condition of an actuator, but will also reduce false alarms.

2. Decision-Making Based Condition Based Maintenance

The DM/CBM algorithm is a detailed in Figure 1 [8].

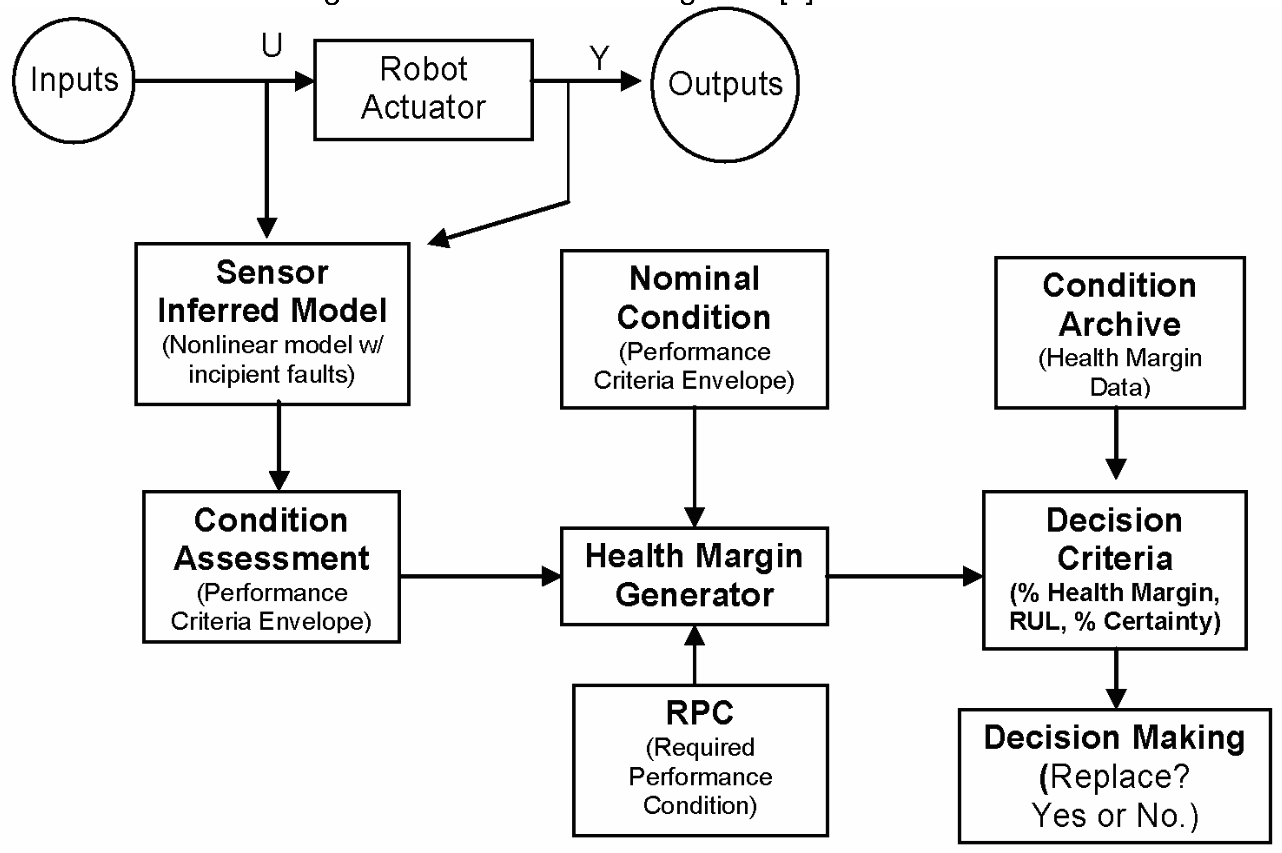


Figure 1. DM/CBM detailed flow chart [8].

Before starting the DM/CBM process, a set of task performance criteria must be selected (e.g. torque and speed). At a minimum, the performance criteria used for DM/CBM should match the criteria that were originally used in selecting the actuator. The selected performance criteria are the axes of the performance envelope describing the actuator's Nominal Performance Condition (NPC) (nominal condition is used to refer to the condition at purchase), Assessed Performance Condition (APC) and its Required Performance Condition (RPC).

The first part of the DM/CBM flowchart invokes the same principle of analytical redundancy that general model-based FDI (Failure Detection and Isolation) strategies use. A state/parameter estimator based on an accurate nonlinear actuator model is assumed to be available and convergent. This describes the sensor inferred model, which is the first block in the flow chart. For the general class of incipient faults, the sensor inferred model is used to map dynamically changing sensor data to a fault-sensitive model of the actuator, which reflects the actuator's current condition. The sensor inferred model block continuously receives sensor signals that measure the inputs and outputs of the actuator, updating the estimate of the model parameters.

The output of the sensor inferred model block is the vector of parametric constants that characterize the actuator model. Although the actuator model is time invariant, incipient faults cause gradual changes in the model parameters. Depending on the type of parameter estimator used, a forgetting factor will be needed to track the model parameters in a quasi-static manner.

The word condition is ambiguous in the literature, at least in the context of incipient faults (in the case of abrupt faults, the condition may be assessed in a binary way: fault or no fault). In response to this ambiguity, were used performance envelopes for defining condition. Based on the observed model with its continuously updated parameters, the condition of the actuator is updated. This condition is called the Assessed Performance Condition (APC). Specifically, the model is used to generate an updated envelope for all of the pertinent performance criteria. By allowing the operator to choose which criteria are important, the condition of the actuator is assessed in a way that is meaningful to the operator and is useful for making decisions.

Assessed Performance Condition (APC) is the performance envelope, whose axes are the task-specific performance criteria (chosen by the operator), describing the most current range of operating capabilities for the actuator. The threshold for declaring an abrupt fault is usually determined using a statistical threshold, a level of confidence. This is not the case for incipient faults which are gradual in their progression. There is no accepted way to determine when a fault is too big to ignore.

Continuing to move through the flow chart, health margin generation is the next step. At this point, the condition has been assessed, but it is still useless for decision-making without some reference for comparison. The health margin results from comparing the APC with the Nominal Performance Condition (NPC) and the Required Performance Condition (RPC) as the system degrades. Each of these envelopes is defined next:

Nominal Performance Condition (NPC) is the performance envelope, whose axes are the task-specific performance criteria (chosen by the operator), describing the range of operating capabilities for the actuator when it was brand new (i.e. zero degradation).

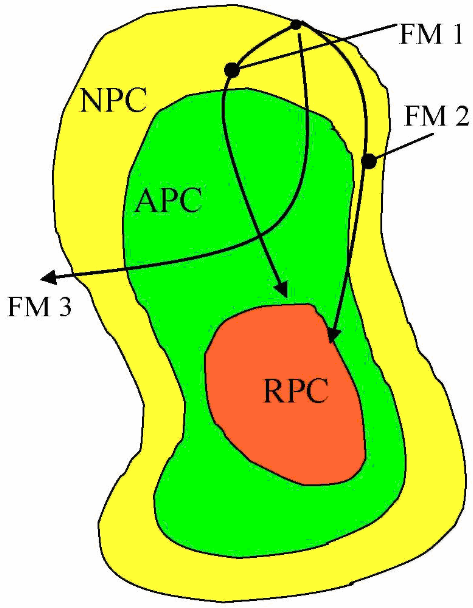
Required Performance Condition (RPC) is the performance envelope, whose axes are the task-specific performance criteria (chosen by the operator), describing the minimum range of operating points necessary to meet the task requirements.

The operator can generate an RPC by scaling each dimension of the actuator's nominal performance envelope and will be called a vector RPC. If the operator is willing to provide a matrix of information about the RPC, then very meaningful residuals can be generated and will be called array RPC. While an array RPC offers the best results for CBM decision-making, it comes at a much higher price than vector RPCs. In order to define an array RPC, the operator must either possess historical process data or simulation data that fully defines how an actuator is used for the specific application.

Recalling that we desire to meet the prerequisites for a decision-making algorithm given by [5], the RPC fulfills the first point–the task description. The RPC is analogous to the task description in the decision-making protocol because it provides a quantitative description of the task to be performed.

Figure 2 shows, conceptually, the components needed to compute the health margin for a generic system. The outermost envelope is the NPC envelope. This represents the condition of the system as it was when it was brand new (i.e. zero degradation). The APC is the envelope that is interior to the NPC. The dark envelope in the center is the RPC, which bounds the task demands. The three curved lines represent the trajectory of a single point, which was originally located on the NPC, but as a result of degradation, moves with time. Each of the lines is labeled 'FM' to indicate 'failure mode.' Each failure mode has its own unique trajectory associated with every point on the NPC. Note that while failure modes 1 and 2 result in a breach of the RPC (a functional fault), failure mode 3 never does. Furthermore, if two failure modes act simultaneously, their trajectories will be combined (though probably not linearly). This is illustrated in Figure 3.

Ideally, the health margin would be calculated by taking the ratio of the remaining length along the trajectory to the total length along the trajectory. This ratio can be calculated at each point on the NPC, so the health margin is an array of ratios (if the health margin was captured for all time as the system degraded (due to a single fault), it would be a vector field). Since it is not scalar, it must be further distilled for decision making.



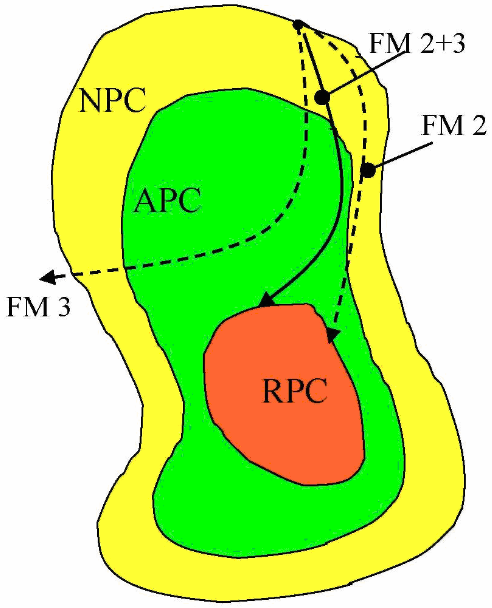
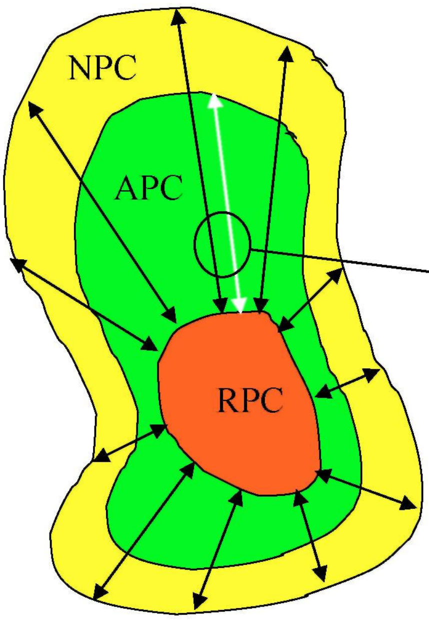


Figure 2. Trajectories for Individual Failure [8] ***Figure 3. Trajectory for a Simultaneous Failure [8]***

For the ideal definition of health margin to be viable, the failure mode and corresponding trajectory must be known when the machine is in its nominal condition. Since the failure mode(s) of a real life machine is uncertain, a means of estimation is required if health margin is to be calculated. Figure 4 illustrates the estimated health margin calculation that is suggested by the authors. Here the failure mode trajectory is ignored in favor of the direction normal to the RPC.



$$HM_i \approx \frac{\|white \quad arrow\|}{\|black \quad arrow\|}$$

or

$$HM_i \approx \frac{\|APC - RPC\|}{\|NPC - RPC\|}$$

Figure 4. Approximated Health Margin Graphic [8]

In order to make the decision about whether to declare an actuator healthy or faulty, decision-making criteria are needed. These criteria are categorized such that they are aligned with the operator's chief concerns: Can the actuator provide the desired performance at present, what is the estimated time before it can no longer provide the desired level of performance, and how certain are the estimates about the former criteria? In accordance with each respective concern, the decision criteria have been named % Health Margin (%HM), Remaining Useful Life (RUL), and % Certainty. Specific quantitative definitions of each decision criteria type will be considered next. Although these criteria definitions are intended to encompass as many actuator applications as possible, there are bound to be applications (unknown to us at this time) that would be better served by an application-specific criterion. Additions to these definitions are expected for that reason.

For calculating the health margin data (which took the form of an array), two choices have been identified for varying the definition of % health margin. First, the way the RPC is defined changes the calculated %HM criterion. Second, the way in which the multidimensional health margin data is condensed (to a scalar) affects the %HM criterion. The result of this process shall be referred to as a norm (2). They are merely norms in the sense that a scalar value results from an operation on a multidimensional matrix of data.

Remaining Useful Life (RUL) is a prognostic estimate of the time before %HM reaches zero. Ideally, this would be calculated by isolating which fault is occurring and then using historical knowledge (from a data base or a model) to relate the present condition and anticipated operating regime to the future trajectory of that particular fault-related condition. However, at this early stage in the maturity of DM/CBM, a much less demanding (and less accurate) approach will be taken. As a first approach, the current %HM and its time derivative are used to make a linear approximation of the time before %HM reaches zero.

Figure 5 [8] shows a hypothetical example of the progress of the assessed condition as the system degrades. Each curve represents the assessed condition of the system calculated on a constant time interval. This corresponds to Figure 6 [8], in which minimum %HM decreases toward zero. Each red do marks the minimum %HM at each time the condition is assessed. In this example (not in general), the minimum health margin decreases rapidly at first, corresponding to the large gaps between red dots, and then slows slightly as it approaches 0% health margin, corresponding to the smaller gaps between the red dots.

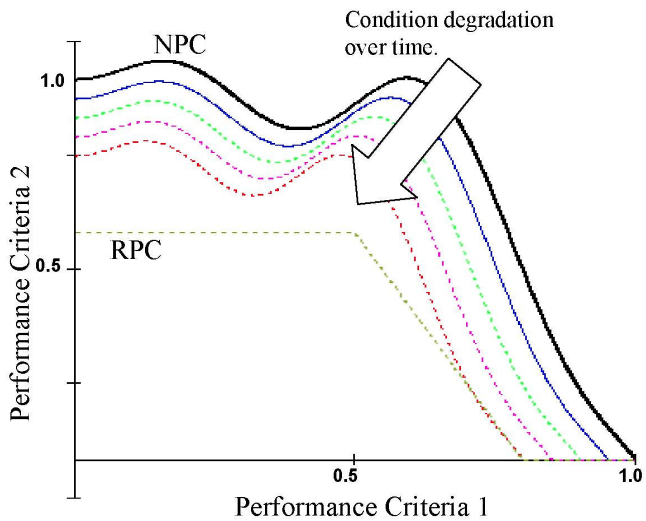


Figure 5. Assessed condition degradation [8].

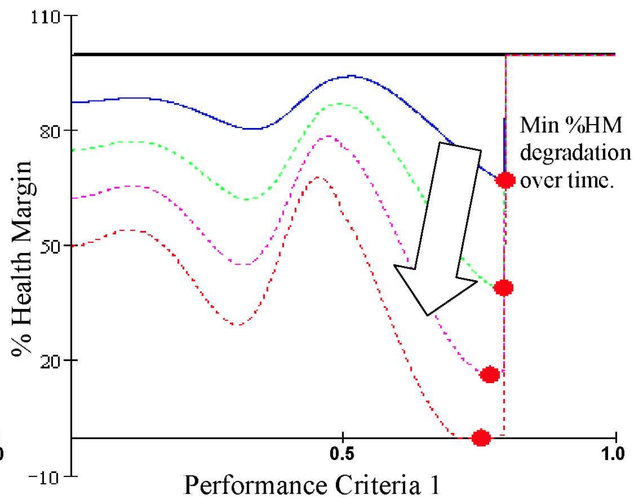


Figure 6. Minimum %HM degradation [8].

As DM/CBM matures, time/operating regime models of prominent failure modes could be included to increase the accuracy of the estimated time to failure. Inclusion of these models would be especially helpful for fault modes that occur non-linearly. Besides the accurate estimation of the condition of a system, the fault prognosis (RUL) is the most important piece of information in the fault decision process. Statistical methods are needed to establish the certainty for DM/CBM. Statistical certainty often serves as the only threshold for detecting/deciding if a fault has occurred [1]. Statistical certainty is augmented by %HM and RUL in making the fault decision. This characteristic improves the decision logic so those fault magnitude and fault prognoses are taken into account.

A CBM method capable of monitoring a broad variety of systems and subsystems would be preferable to a method that works for special cases only. Persistent activity is basically the requirement that the system inputs be non-stationary and that they excite all of the modes of the model. Though this is necessary in the sensor inferred model stage, it is even more important for the condition assessment stage which is considered next.

Proceeding to the condition assessment stage, persistent activity must exist for this process to work fully as well. If the system is persistently active, then the performance criteria will vary substantially over the range of operation. The reason that performance envelopes are used in the first place is that they capture performance degradation over the entire operating regime, and not just at the local point of operation. For steady state systems, the single-point residual methods used by the FDI are more than adequate.

Moving on to the health margin generation stage, one further requirement is added. If the RPC is equal to or greater than the NPC of the system, then even the slightest degradation will trigger the fault decision. The RPC is vital for the decision-making process and the better RPC is known, the more the final fault decision can be trusted. The %HM criterion should be selected so as to avoid singularities near zero. The minimum RUL must not be large in comparison to the rate of system degradation. Is no benefit applying DM/CBM to a system whose failure modes occur more rapidly than the maintenance crew can respond.

3. SUMMARY

Prognostic information is the most important information provided by any CBM system because it enables the prediction of future performance deficiencies, and thus facilitates preemptive maintenance. In DM/CBM, RUL is the prognostic decision criterion. Without the capability to forecast the future condition of the actuator, DM/CBM would be little more than a cumbersome fault detection method. Real-world fault progression is completely dependent on the failure mode, which is often state dependent or at least nonlinear in time. The best way to cope with this would be to make a diagnosis about the dominant failure modes and then use archived or expert prognostic models to predict the implications for the future fault progression.

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