AUTONOMOUS PROGNOSTIC MONITORING DEVICE

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Abstract: A new device for monitoring the environmental and operational stress profiles of products used in a wide range of environmental conditions has been developed. This device, as small as a typical credit card, is capable of recording and transmitting environmental and operational stress data. Prognostic and health monitoring models and algorithms can use this data to do prognostics of the monitored systems. This paper presents details of the construction and application of this monitoring device. Data of a field test are analyzed by sequential probability ratio test to demonstrate the failure prediction methodology.

Keywords: Prognostic and health monitoring; ePrognostic sensor system

Prognostics and Health Monitoring: Prognostics and health management (PHM) is a method that permits the reliability of a system to be evaluated in its actual life-cycle conditions to determine the advent of failure and mitigate the system risks [1]. PHM techniques combine sensing and interpretation of environmental, operational, and performance-related parameters. These parameters are indicative of a system’s health including any performance degradation, such as deviation of operating parameters from their expected values; the physical or electrical degradation, such as material cracking, corrosion, interfacial delaminating, increase in electrical resistance or threshold voltage; or the changes in a life cycle environment, such as usage duration and frequency, ambient temperature and humidity, vibration and shock [2]. Based on this information, PHM can provide advanced warning of failures; can reduce life cycle cost of the product by decreasing inspection costs, downtime, and inventory; and can assist in the design and logistical support of fielded and future products[1].

The importance of PHM implementation was explicitly stated in the DoD 5000.2 policy document on defense acquisition, which states that “program managers shall optimize operational readiness through affordable, integrated, embedded diagnostics and prognostics, and embedded training and testing, serialized item management, automatic identification technology (AIT), and iterative technology refreshment” [3].

PHM methodology is based on monitoring parameters that are sensitive to failure precursors that indicate impending failure. A precursor is usually a change in a measurable variable that can be associated with subsequent failure. For example, a shift in the output voltage of a power supply might suggest impending failure due to a degrading feedback regulator circuitry. Failures can then be predicted by using a causal relationship between a measured variable that can be correlated with subsequent failure [4]. In general, to implement a precursor reasoning-based PHM system, it is necessary to identify the parameters, which may indicate the failure occurrence, and monitor them,
then develop a reasoning algorithm to correlate the change in these parameters with the impending failure. Based on these correlations, algorithms may predict the failure in advance.

In the stress-damage prognostics approach, the extent and rate of product degradation depends upon the magnitude and duration of exposure to loads (usage rate, frequency, and severity). In this approach the life-cycle loads are monitored in-situ, and used in conjunction with PoF-based damage models to assess the degradation due to cumulative load exposures. The life-cycle loads of a product can be generated from manufacturing, shipment, storage, handling, operating and non-operating conditions. The life-cycle loads (thermal, mechanical, chemical, electrical, and so on), either individually or in various combinations, can lead to performance or physical degradation of the product and reduce its service life.

Both the failure precursor prognostics method and the stress-damage prognostics approach need sensor systems to monitor the corresponding parameters. The CALCE-ePrognostic sensor system is a novel monitoring device which can monitor the parameters used for prognostics such as temperature, humidity, and vibration. Compared with traditional sensor systems, it is wireless and can be mounted in the host system easily and non-intrusively. In this paper, a case that uses the ePrognostic sensor tag to monitor the temperature loads on un-manned army vehicles is provided to demonstrate the utility of the monitor device.

**Autonomous Prognostics Monitoring Device:** The Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland, in cooperation with ePrognostic Systems (a company based in Austin, Texas) developed an autonomous prognostics monitoring device, CALCE-ePrognostic sensor system, which consists of a radio frequency identification (RFID) tag, reader, and CALCE prognostic software. The tag is small, self-sealed and flexible. The dimensions are 76mm x 63mm x 2.5mm (3.5” x 2.0” x 0.1”), which is similar in size to a typical credit card, shown in Fig. 1. The processor, memory and data communications electronics were integrated into a single chip, which is sealed from moisture and dust in laminated layers. The tag carries its own power supply in a wafer thin battery, also flexible and sealed in the laminated layers. The communication of the signal is wireless and based on RFID technology. These characteristics enable the tag to be used in a harsh environment and make it non-intrusive to the host. The adhesive used to mount the sensor tags is about as sticky as brown packing tape. The tags weigh approximately 15g and are flexible; they stick very well to the surface, even the curved surface.
The CALCE prognostic software is used in the computer to control the reader that connects with the computer by USB port, and provide the prognostic analysis of the data. When the tag is in the RF (Radio Frequency) field of the reader, it can be identified, activated and configured wirelessly. The user can program the sampling mode and rate based on the specific applications. After activation and configuration, the tag works independently and automatically. The built-in battery will power the embedded multiple sensors to monitor and record the corresponding data on temperature, humidity, acoustic and 3-D accelerometer. The data can be saved in the onboard memory and then be identified and transmitted wirelessly by the reader to the computer. The software also analyzes the data using the prognostic technology and algorithms to provide the detection and prediction functions.

RFID technology makes the sensor tag programming and the data communication wireless. The operating frequency of the sensor tag's RFID is 13.56 MHz. The range of the transmission is related to the radio frequency. The tag is activated by the reader, and then it actively monitors and records the data, but it does not send the data out until it receives a requiring signal from the reader. However, for the proposal, we have the technology now to enable variable reading distance and also the ability to turn the wireless function off and use LED indicators.

Before the tag is used, it must be programmed to set the sample rate and mode. For our sensor tag, multiple options will be available to maximize the utility for the data collection and reporting. First, for the data acquisition, the time interval between consecutive readings is programmable. Using the variable (e.g. temperature) monitoring as an example, the sampling intervals can be seconds, minutes, or hours. Since there is a limit to the number of memory locations allocated to data storage, this interval selection is important relative to the total elapsed time. Currently, the maximum recording duration is about 4-weeks at 30-minute sample intervals.

The sensor tag allows a user to specify upper and/or lower thresholds, thereby increasing the utility of the data storage memory. For example, if the monitored device is more sensitive to temperature cycles that exceed 45 °C, there is an option to only record the temperature samples that exceed a preset threshold (45 °C in this case). Simultaneously, there is an option to set a lower threshold value, for example freezing (0 °C). If both thresholds are set as high limit of 45 °C and low limit of 0 °C, only temperature samples above 45 °C and samples below 0 °C will be recorded into the memory. This will eliminate unnecessary recordings and memory usage between the two temperature limits.
In applications where the equipment sits idle much of the time, those idle readings will not consume valuable memory space.

Another useful programming feature is “delayed start”. If a user knows there will be some delay time between installation and operation, the user can opt to save memory space wasted by samples taken during that delay by specifying a “delayed start” time in units of minutes, hours or days. The ePrognostic sensor tag software includes a convenient calculation tool that allows a user to select a calendar date and time of day, which will automatically calculate and program the correct delay time. Included in our roadmap is a patent-pending method to select “mounting time start” as an option. This is particularly valuable when there are several other variables that dictate the start of a test and will help to avoid the monitoring process to either start too soon or start too late and miss critical data.

After the tag has been programmed, it can monitor and record the temperature autonomously. The onboard battery allows the tag to operate for up to approximately 20,000 logging cycles (the equivalent of 1 year). The maximum memory capacity is 720 data points. Each point includes the monitored value and the time stamp. Each tag has a unique identification number which enables the reader to distinguish each tag when multiple tags are being used.

**Data Acquisition Using ePrognostic Sensor Tag:** The US Army has a project named “SWORDS”, which involves a remote-controlled roving vehicle that is small enough to navigate through narrow passageways such as hallways and stairways in buildings, as well as travel in diverse and harsh environments such as hot, dry deserts or cold, wet climates. Since the vehicle is remotely controlled and contains multiple cameras and electromechanical devices, it carries a lot of electronics as well as electrically operated motors and servos. Given the desire to keep the overall vehicle very small, all these devices are compact. Fig. 2 is a photograph of the SWORDS vehicle.

![Fig. 2 SWORDS Vehicle](image)

To provide a complete environmental stress profile of the vehicle, it was required that a monitoring device be incorporated onto the vehicle to record the environmental stress on the vehicle while in shipment (aircraft or ship cargo) and to record the operational environment. Though the temperature condition is of primary interest, shock and
vibration cannot be ignored. This required reliable non-intrusive, small-volume measurement devices that can survive in a wide range of temperature and vibration environments. Fig. 3 shows photos of mounting locations on SWORDS.

![Fig. 3: ePrognostic sensor tags* Mounted on the SWORDS Vehicle](image)

![Fig. 4: Raw Data Captured by ePrognostic sensor tag](image)

A field test was conducted using the ePrognostic sensor tags. With a requested 2-day lead-time to the first operational test of the SWORDS vehicle, two sets of three ePrognostic sensor tags were programmed and shipped to the test site where they were

* The tags in this picture are different with that in Fig. 1. The tag in Fig. 1 is the latest one.
placed on two SWORDS vehicles. They were attached to the vehicles by peeling off their protective paper layer and pressing them onto a flat or slightly curved surface of the vehicle: no screws, no programming, no switches to set, and no power to provide or connect. Three ePrognostic sensor tags were used in this test resulting in three sets of data. As an example, Fig. 4 only shows the raw data of temperature collected by the ePrognostic sensor tags. The sample dates are on the horizontal axis and temperature in degrees Celsius is on the vertical axis. The interval of temperature sampling was 30-minutes and all samples were recorded (no high/low thresholds were used).

**Prognostic approach:** When data from the sensor tag is transferred to the host computer, a prognostic approach is used to analyze the data. In this paper, the prognostic approach focuses on anomaly detection in advance. This approach includes a training procedure and a detection procedure. In the training procedure, the algorithm learns the features of the monitored device in the healthy situation. The training data can be obtained from historic data or from the initial operation phases when the device is known to be healthy. The Features, such as the distribution, of the training data is extracted, based on a detection baseline which is created. In the detection procedure, the corresponding features of the test data are compared with the baseline to detect the anomalies. One of the detection methods is called sequential probability ratio test (SPRT), which is very sensitive to the data change. Under certain false alarm probability and missed alarm probability, SPRT gives a decision, with minimized sampling, detecting the anomalies at their insipient stage prior to developing into failure. In this paper, SPRT is used to process the ePrognostic data collected on the SWORDS vehicle as a prognostic demonstration. Shown in Fig. 4, we define that if the temperature data collected by tags exceed 35 °C, an alarm is given, we call this as actual alarm. If SPRT can detect the anomaly and give an alarm in advance, it will be suitable for prognostics. The time difference between the alarm given by SPRT and the actual alarm is defined as the prognostic distance, which can be used to evaluate the prognostic ability.

SPRT is a statistical binary hypothesis test which allows the detection of statistical changes in noisy signals at the earliest possible time. It is based on a statistical process control method introduced by Wald in 1947[7]. SPRT analyzes observations sequentially to determine whether or not the signal is within the known normal behavior of the system. The binary hypothesis includes one null hypothesis and one or more alternative hypothesis. For normal distribution, the null hypothesis $H_0$ is the hypothesis for healthy state, under which the test data are normal distribution with mean=$0$ and standard deviation=$\sigma$; the alternative hypothesis $H_j$ is the hypothesis for abnormal state, under which the test data are normal distribution with mean$\neq0$, or standard deviation $\neq\sigma$. The alternative hypothesis includes four situations: 1) $H_1$: the mean of the test data has shifted high to $+M$; 2) $H_2$: the mean of the test data has shifted low to $-M$; 3) $H_3$: the variance of test data has increased to $V\sigma^2$; 4) $H_4$: the variance of test data has decreased to $\sigma^2/V$. $M$, $V$ are the predetermined system disturbance magnitudes, which are decided by users. $M$ is often several times of the standard deviation of the data in healthy situation.

For each alternative hypothesis, SPRT will calculate the SPRT index and then compare with certain thresholds. The SPRT index is the nature logarithm of the ratio of the probability that the data accepts the null hypothesis to the probability that the data accepts the alternative hypothesis.
where, $SPRT_j$ is the SPRT index, $LR_j$ means likelihood ratio, for independent process,

$$LR_j = \frac{\text{probability of sequence } \{X_{n}\} \text{ given } H_j \text{ true}}{\text{probability of sequence } \{X_{n}\} \text{ given } H_0 \text{ true}} = \prod_{i=1}^{n} \frac{\Pr(x_i|H_j)}{\Pr(x_i|H_0)} = \prod_{i=1}^{n} \frac{f_j(x_i)}{f_0(x_i)}$$

(2)

SPRT uses the probabilities of missed alarms and false alarms to specify the thresholds of acceptance and rejection of the null hypothesis. False alarm probability, $\alpha$, occurs when $H_0$ is rejected even though it is true while missed alarm, $\beta$, occurs when $H_0$ is accepted while it is in reality false.

$$A = \ln\left(\frac{\beta}{1-\alpha}\right), \quad B = \ln\left(\frac{1-\beta}{\alpha}\right)$$

(3)

Fig. 5 shows the procedure of SPRT. At the beginning, all four SPRT indices are set to 0. Then, when data is collected, the SPRT indices are updated using the appropriate SPRT equations. Each SPRT index is then compared to the decision boundaries (A, B). For each comparison, there are three possible outcomes: 1) the lower limit is reached, in which case the process is declared healthy under the specific hypothesis test, the corresponding index is reset to zero, and sampling continues; 2) the upper limit is reached, in which case the alarm is given, the corresponding index is reset to zero, and sampling continues; or, 3) neither limit has been reached, in which case the information is not sufficient to make a conclusion, and the sampling continues. The comparison of the four SPRT indices with limits is parallel and this procedure ensures that an alarm will be generated when any of the four SPRT indices reach the upper limit.

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**Results:** Fig. 6 shows the results of the SPRT analysis of the data in Fig. 4. The data from ePrognostic sensor tag C1 and C2 are considered as training data. Data of tag C3 is the test data which is processed by SPRT. SPRT extracts the features of the training date, such as the mean and standard deviation. The test data is normalized by subtracting the mean of the training data. System disturbance magnitude, $M$, is 5 times of standard deviation of the training data; the variation factor $V$ is 2, the false alarm probability is 5%,
and missed alarm probability is 10%. Fig. 6 shows that all anomalies occurred because the test data deviate from the mean of the healthy status.

![Detection results of individual SPRT test](image)

**Fig. 6: Detection results of individual SPRT test**

The comparison of the alarm time detected by SPRT with those given by the raw data is shown in Fig. 7. The points in the Fig. are detected as anomalies by SPRT. These points are from the detection results shown in Fig. 6. Table I shows the prognostic distances in area A, B, C and D. The prognostic distance is defined as the time difference between the SPRT detection and the simulated alarm, for example, in area A, SPRT can give an alarm 30 minutes ahead of the simulated alarm, thus the prognostic distance is 30 minutes. In the area D, SPRT gives a false alarm. This is because in this detection, the false alarm probability is set as 0.05, which means 5% false alarm is allowed in this specific application.

Based on the results, we see that as an anomaly detection algorithm essentially, SPRT can not give a long prognostic distance in the raw data analysis. But SPRT is very sensitive to the data change, thus if we conduct some preprocessing to the data, and extract some other parameters, such as the temperature change rate, and then use SPRT to do the detection, the prognostic distance will be improved much longer, thus it will have enough time to take some actions to reduce the effect of the anomalies.
Fig. 7: Raw data of Tag C3 and the alarms detected by SPRT

Table I: Prognostic distances

<table>
<thead>
<tr>
<th></th>
<th>Earliest SPRT Alarm (hrs)</th>
<th>Earliest Simulated Alarm (hrs)</th>
<th>Prognostic Distance (hrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20</td>
<td>20.5</td>
<td>0.5</td>
</tr>
<tr>
<td>B</td>
<td>41</td>
<td>45</td>
<td>4</td>
</tr>
<tr>
<td>C</td>
<td>159</td>
<td>165.5</td>
<td>6.5</td>
</tr>
<tr>
<td>D</td>
<td>333</td>
<td>None</td>
<td>None</td>
</tr>
</tbody>
</table>

Summary: An autonomous prognostics monitoring device, CALCE-ePrognostic sensor system, is introduced in this paper. The properties of the device, such as the multiple sensors that can monitor the temperature, humidity and vibration, the on-board battery and memory, RFID wireless data transmission, and the small and flexible shape, enable it to monitor the environmental and operational stress of the host automatically and non-intrusively. The CALCE-ePrognostic Sensor system was used in the SWORDS project. The data collected by the sensor tag were analyzed by a prognostic approach, in which SPRT was used to detect the anomaly based on the training by the data collected under the healthy situation. The results show that ePrognostic sensor tag combining with SPRT has the ability to detect the anomaly and provide an alarm before the actual failure occurs. In the future, with more built-in multiple sensing elements and more advanced prognostic algorithms, CALCE-ePrognostic system can monitor and predict the status of the monitored systems more accurately.

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References


