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Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques —

Part 2:
Data-driven applications

Surveillance et diagnostic d'état des machines — Interprétation des données et techniques de diagnostic —

Partie 2: Systèmes guidés par les données

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Foreword

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The procedures used to develop this document and those intended for its further maintenance are described in the ISO/IEC Directives, Part 1. In particular the different approval criteria needed for the different types of ISO documents should be noted. This document was drafted in accordance with the editorial rules of the ISO/IEC Directives, Part 2 (see www.iso.org/directives).

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For an explanation on the meaning of ISO specific terms and expressions related to conformity assessment, as well as information about ISO's adherence to the WTO principles in the Technical Barriers to Trade (TBT), see the following URL: Foreword - Supplementary information.

The committee responsible for this document is ISO/TC 108, *Mechanical vibration, shock and condition monitoring*, Subcommittee SC 5, *Condition monitoring and diagnostics of machine systems*.

ISO 13379 consists of the following parts, under the general title *Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques*:

— *Part 1: General guidelines*

— *Part 2: Data-driven applications*

— *Part 3: Knowledge-based applications*

Introduction

This part of ISO 13379 contains general procedures that can be used to determine the condition of a machine relative to a set of baseline parameters. Changes from the baseline values and comparison to alarm criteria are used to indicate anomalous behaviour and to generate alarms: this is usually designated as condition monitoring. Additionally, procedures that identify the cause(s) of the anomalous behaviour are given in order to assist in the determination of the proper corrective action: this is usually designated as diagnostics.

Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques —

Part 2:
Data-driven applications

1 Scope

This part of ISO 13379 gives procedures to implement data-driven monitoring and diagnostic methods to facilitate the work of analysis carried out by specialist staff typically located in a monitoring centre.

Although some of the steps are embedded in existing tools, it is essential to be aware of the following steps for optimum use:

— selection of the asset, the critical failures and the available process parameters;

— data cleaning and resampling;

— model development;

— model initialization and tuning;

— model performance evaluation;

— diagnostics process.

The implementation of these steps does not require a thorough knowledge of the statistical methods. It does require the competence first to build the training models and then to carry out monitoring and diagnostics processes.

The training in data-driven monitoring is carried out on equipment that is exhibiting normal behaviour. In that case, the principle of fault detection is to compare observed data to estimated data. A difference (called residuals) between an observed and expected values of the parameters reveals the presence of an anomaly, which can be related either to equipment or instrument.

The training in data-driven diagnosis is carried out both on equipment that is exhibiting normal behaviour and failures. The principle of the method is not to detect the deviation of a parameter but to identify a fault by comparison of the observed situation to the faults learnt during the training phase. The technique usually applied is pattern recognition followed by pattern classification.

Data can be available from the data historian of the distributed control system (DCS) or from specialized monitoring systems.

2 Normative references

The following documents, in whole or in part, are normatively referenced in this document and are indispensable for its application. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

ISO 13372, *Condition monitoring and diagnostics of machines — Vocabulary*

ISO 13379-1, *Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques — Part 1: General guidelines*

3 Terms and definitions

For the purposes of this document, the terms and definitions given in ISO 13372 and ISO 13379-1 apply.

4 Procedure to implement data-driven monitoring

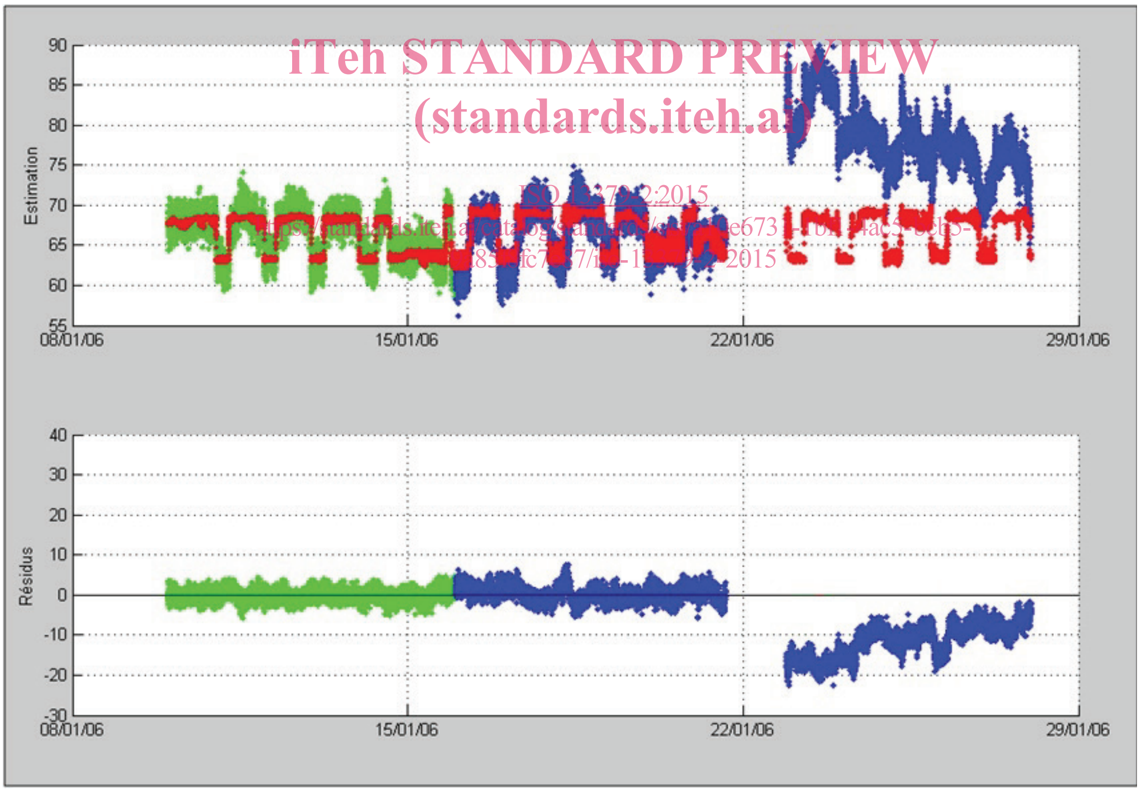
4.1 Principle of data-driven monitoring methods

Advanced statistical methods that simultaneously consider multiple plant signals and model the underlying relationship between them are beginning to replace the classical methods for condition monitoring which are based on the observation of trends of individual signals.

These monitoring methods rely on the same principle to detect a fault, which is to compare observed data to estimated data.

Prior to the monitoring phase, it is required to build the model of the normal equipment behaviour, during a training phase. Faults can thus often be detected as deviations between an observed and an expected value of the parameters of the system.

Figure 1 shows an example of an application on a gas turbine. The objective is to detect abnormal shaft displacements after a shut down. Several inputs are considered in the model: active and reactive power and bearing displacements.



Key

green training
blue monitoring
red prediction

Figure 1 — Gas turbine displacement magnitude and residual

Data-driven monitoring methods generally applied are Auto associative kernel regression (AAKR), cluster and partial least square (PLS), support vector machine (SVM), and/or Mahalanobis-Taguchi (MT) methods.

4.2 Asset critical failures and process parameters selection

The procedure for the implementation of data-driven monitoring is precisely described in ISO 17359. It includes two main audits:

— equipment audit: identify equipment and its function;

— reliability and criticality audit: produce a reliability block diagram, establish equipment criticality and perform failure modes, effects and criticality analysis.

Once this preliminary study is carried out and the list of the critical faults is identified, it is necessary to list the process data available in the data historian or in specialized monitoring systems. An example would be a vibration monitoring system.

It might be necessary to consider the installation of additional sensors or location of existing sensors if the detection scope of the critical faults is not completely covered.

4.3 Data cleaning and resampling

4.3.1 General

In order to build a robust model, one shall first collect data covering all the operating conditions in which the system is expected to run and for which signal validation is desired. These data are historical data that have been collected and stored. In fact, they might not always represent the real plant state due to several anomalies that commonly occur, including interpolation errors, random data errors, missing data, loss of significant figures, stuck data, and others. Data should always be checked and corrected.

WARNING — Caution shall be taken before deleting data.

4.3.2 Interpolation errors

The first problem usually encountered when using historical data for model training is that available conditioned data do not correspond to actual data, but instead, data resulting from compression routines normally implemented in data archival programs. Generally, the data historian creates a data archive that is a time series database. However, all of the data are not stored at each collection time. Only data values that have changed by more than a specified tolerance are stored along with their time stamp. This method requires much less storage but results in a loss of data fidelity. When data are extracted from the historian, data values between logged data points are calculated through either a simple linear interpolation or a step at the time of the second data point. The resulting data appear to be a saw-tooth time series and the correlations between sensors might be severely changed.

As a conclusion, data collected for model training should be actual data and tolerances should be set as small as possible or not used.

4.3.3 Data quality issues

Several of the most common data quality issues are:

— missing data;

— noisy or random data;

— defective sensors for which the data value is not updated or is out of calibration;

— unreasonable data values (out of range).

Most of these data problems can be visually identified or can be detected by a data clean-up utility. These utilities remove bad data or replace it with the most probable data value using an algorithm. It is most common to delete all bad data observations from the training data set. Most software systems include automated tools for data clean-up; these tools easily identify extreme outlying data but are typically insensitive to data errors that occur within the expected region of operation. The addition of bad data points in a training set can invalidate a model.

4.3.4 Data resampling

Once the data have been cleaned, it might be necessary to resample the data at a lower rate determined by the selected operation modes. Thus, it is advised to keep all the time stamps to characterize the transients of the significant operating parameters (e.g. run down of a machine) whereas under steady-state operation, a sample every 10 min (obtained by average or not) might be sufficient.

4.4 Model development

4.4.1 General

Model development is not trivial. There are several steps that need to be performed including:

— selecting relevant features;

— selecting relevant operating regions and training data;

— preparing the model tests.

Construction of a data-driven model requires:

— a set of parameters (sensors) which focus on a specific type of fault (mechanical, electrical, thermal, etc.);

— data samples for a period during which the machine is known to be in good health.

4.4.2 Definition of models and selection of relevant inputs

Once the quality of the data has been validated, model features shall be defined. Features may be the raw sensor values themselves or derived from the sensor values (exponentially weighted moving averages, means, kurtosis, etc.). A large process plant may possess hundreds of parameters that require monitoring for the assessment of critical equipment. Hence, they shall be divided into smaller correlated groups to focus on a specific function of the equipment (thermal, mechanical, cooling, etc.).

Model performance can be strongly affected by the features included. Unnecessary features tend to reduce performance by inducing false alarms or masking real events. Unnecessary features may include non-varying or random features. Missing important features can make some faults impossible to detect.

To obtain accuracy and robustness when building a model, features should be selected bearing in mind the functional aspect (parameters useful for detection of a specific group of faults) as well as the numerical aspect. It is recommended to employ correlated features in the model and to consider the fact that normal change of the machine condition can be explained by an independent parameter of the equipment (such as external process parameters).

4.4.3 Selection of relevant operating conditions and data

The model shall be trained with data covering all operating conditions in which it is expected to be applied. These operating regions can vary significantly between plants since they are defined by system structure, sensor values, and operating procedures.

One example of an operating condition change is the periodic usage of standby pumps or the cycled usage of redundant pumps. A model shall be trained for each operating condition of the system to work properly, but excessive training on unusual conditions might degrade the performance on the most usual operating conditions. Therefore, some plant line-ups might never be included in the training set.

Operating conditions can also change as a result of equipment repair. In this case, the model shall be retrained to account for the new condition.

Finally, operating conditions also change due to cyclic phenomena, such as seasonal variations. If a model is trained on data collected in the summer, it might not perform well in the winter when the temperature of the air, cooling water, etc. are significantly different. Additionally, unusual variation in ambient conditions might affect model performance, e.g. if a model is trained using typical summer data, and then applied during an unusually hot summer with higher cooling water temperatures, the model might not perform correctly. In this case, data from the new operating conditions shall be added to the training data.

Some particular operating conditions to keep in mind are the following.

— Times when the machine has been serviced should be noted because maintenance might cause significant changes of performance.

— It is necessary to account for machines which have very long intervals between maintenance and that show significant normal deterioration in performance.

— When building a model, be aware of the impact of preceding transients on the current behaviour (for example preceding power or speed changes).

4.4.4 Preparation of the model tests

Once all typical operating regions are identified, the next step is to select the input data and to divide the data between training, validation, and test observations. Generally, the user does not have the choice of the underlying classification method since it depends on the monitoring tool.

The training and validation data are used to develop and test the model of the process equipment. The test set which consists of the validation model with additional deviations is used to evaluate the model detection performance.

4.5 Model performance evaluation

The next step in the monitoring process is to select and optimize the model parameters, which can differ from one method to another (e.g. kernel bandwidth, maximum cluster diameter, number of Eigen values, number of hidden layers).

Models are trained using the training data and their performance is assessed using the validation data. The model parameters are selected such that performance on the validation data is best. Once the final model parameters have been selected using the training and validation data, the test set can be used to assess how well the model will perform in general. It is important that the test data not be used to tune the model parameters; doing so yields a biased assessment of generalized performance. Additionally, the performance of a model may be assessed when there is sensor drift by applying increasing bias to each sensor reading in turn, and using the model output to correct the sensor faults. The predictions using faulty input data are then used to determine the model's robustness and spillover capabilities. The robustness may be interpreted as a measure of a data-driven model's ability to make correct sensor predictions when the respective sensor value is incorrect due to some sort of fault. Spillover measures the effect a faulty sensor input has on the other sensor predictions.

4.6 Alarm setting

Setting the monitoring model alerts and alarms is a critical task in implementing a successful monitoring application. Setting model alerts is an act of balancing model sensitivity with the probability of missed alarms and the probability of false alarms.

