Anomaly Detection Solutions for Improved Equipment Availability

Big Data is the enabler for Hitachi’s Anomaly Detection Technology

Advances in ICT have made it easy to collect and store massive amounts of operational data for a large number of devices. However, in many cases the data is not being used effectively.

Effective use of this “big data” can provide advance warning of problems and device status changes, leading to higher availability of plant.

Combining our maintenance service expertise with big data mining technology, Hitachi has developed an anomaly detection system.

Benefits of Hitachi’s Anomaly Detection System

01 Reduce Maintenance Cost and Duration
Carrying out maintenance in accordance with equipment status lowers the time and cost of maintenance, improves availability

02 Reduce Unplanned Production Loss
Helps prevent losses from unexpected production facility shutdowns, and improves availability

03 Automated Diagnosis
Equipment status diagnosis previously required manual application of specialist engineering knowledge

04 Enabler for Advanced Maintenance Strategies
Condition-based, risk-based maintenance
Applications

- Predictive Failure Analytics
- Condition Based Maintenance

Conventional Maintenance: Preventive maintenance with periodical inspections and parts replacements. Unexpected failures occur between intervals of periodical maintenance.

Predictive Maintenance: Collects sensor data in real time and predicts potential failures before machines break down.

Anomaly Detection Algorithms

The anomaly detection system uses our Vector quantization clustering (VQC) and local subspace classifier (LSC) algorithms.

These perform machine learning on normal-status sensor data and create indicators of differences between the data to be monitored and the learned normal data group. The system then evaluates whether the result is normal or abnormal.

Traditional Methods such as the Mahalanobis-Taguchi (MT) system can only be applied when sensor data has a normal distribution.

Hitachi’s algorithms are resistant to affects from the data distribution.

Since the algorithms are model-free, they can respond flexibly without the need for model construction or simulations for each status change, even when there is a major change in a device or system operation status.

The optimum system configuration uses each algorithm separately according to the device or system to be monitored, or to the characteristics of the abnormality to be detected.

A drawback of conventional data mining functions is that causes are difficult to explain when diagnosis results are derived from complex sensor signal correlations.

Therefore, the Hitachi system has been designed to simplify the cause analysis by outputting an ordered list of the sensor signals responsible for a detected status change.
Predictive Failure Analytics Approach

- Machine data is automatically diagnosed by the Hitachi’s data mining technology
- The failure signs are then reported to the maintenance service division

Condition-Based Maintenance

Why “Condition-Based Maintenance”? 

- Realize an optimum maintenance plan based on a degradation level
- Minimize maintenance duration and increase operating duration
- Avoid unplanned shutdown by real-time monitoring & diagnosis
- Visualize and share the needs of maintenance by quantifying degradation level

A major challenge of asset operation is to balance reliability and availability
Case Study: Electronics Manufacturing Machinery

Damage of feed bar causes unscheduled stoppage of printing press
• Causes delay of production and spoilage cost.
• Few feed bar spare parts available,
• Procurement and repair is time consuming
• Damage causes damage of expensive moulds

Anomaly Detection Approach
• Collect sensor data from the feed bar via the communication network
• Analyze condition using data from multiple sensors

Features:
• Frequency: 1 press every 5s
• Sensors: acceleration (3 pole), strain gauges
• Sensing, diagnosis on a real-time basis
• Types of presses: ~300

1. Strain & acceleration data are collected regularly.
2. Condition monitoring of the feed bar is displayed on a chart.
3. Just after the initiation of the operation we can determine if the feed bar has become overloaded

Approach to Condition-Based Maintenance
Condition-based maintenance is implemented using a combination of condition diagnosis and risk evaluation, leading to effective maintenance without damage to equipment or over-maintenance.

Traditional Maintenance

<table>
<thead>
<tr>
<th>Corrective Maintenance</th>
<th>Time-Based Maintenance</th>
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<tbody>
<tr>
<td>Maintenance after trouble occurred. High risk of damage or unplanned shutdown caused by degradation.</td>
<td>Periodical maintenance by pre-evaluated lifetime of parts. Maintenance cost is high as condition of parts have no relation.</td>
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Condition-Based Maintenance

Effective maintenance based on the degradation degree of component. Realise high reliability with avoiding damage to equipment and over-maintenance.

Maximisation of availability
Maintenance suitability

The following steps are required to achieve condition-based maintenance

Data cleansing, predictor identification
Through the analysis of equipment data,
✓ Predictor of equipment trip
✓ Degradation of component

Knowledge accumulation
✓ Analysis of operational data
✓ Visualisation of key parameters

Online system deployment
✓ Real-time system diagnosis
✓ Continuous enhancement

Case Study: Electronics Manufacturing Machinery

1 cycle of the operation (initiation to end)
Case Study: Gas Engine Maintenance

Advanced predictive diagnosis technology has been applied to condition based maintenance system for gas engine generators on a commercial basis.

1. Summary of diagnosis results
2. Trends of abnormal levels
3. Trends of sensor data

Maintenance Support Office

- Maintenance support persons
  ① Check summary of diagnosis results on a daily basis
  ②③ Check trends of diagnosis results and sensor data

Submit work orders

Anomaly detected 12 days before machine stops
(Unable to detect until equipment stop by conventional maintenance service)

Suggested failure: Cooling water pressure reduction

Predective maintenance: Oct. 23 (refill water, exchange pump)


Cooling water pressure

Continuous Anomaly detection

12 days before

Oct. 11: Predictive detection
Oct. 23: Predictive maintenance

Trip in 3-4 days (estimated)
Anomaly detected 1 month before machine stops

**Suggested failure: Oil filter differential pressure increase**

Anomaly detection: Dec.30, 2010 - 
Predictive maintenance: Jan.25 (exchange oil filter)


- Lubrication oil pressure: gradual decrease
- Conventional threshold management
- Throttle valve open: gradual decrease

**Anomaly measure**

- Diagnosis stop
- Maintenance
- Learning period
- Continuous Anomaly detection
- Jan.25 Predictive maintenance

**Operation data**

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