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Chemical Plant Key Machinery PdM and Fault Diagnostic

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Abstract: The PdM and fault diagnostic are critical for key machinery reliability excellence in chemical plant. The PdM concept and methodology as well as the case of chemical plant chiller intelligent PdM and fault diagnostic process, progress, benefits, and plan are illustrated in the article.

Keywords: Intelligent PdM (predictive maintenance); Fault diagnostic; Condition monitoring; Chiller; Variables; Big data

1. PdM and Fault Diagnostic in Chemical Plants

PdM (predictive maintenance) is widely applied in the continuous process of chemical plants to assure the reliability.

Predictive maintenance is a condition-driven preventive maintenance program which is the online continuous condition monitoring, analysis, diagnostic with predicting the fault development trend, making the PdM plan for implementation. The condition monitoring and fault diagnostic are the basis of PdM. PdM and fault diagnostic greatly reduces the cost of maintenance. It also improves the product quality, productivity, and profitability of manufacturing and production plants.

There are two types of PdM, the traditional PdM and intelligent (big data or AI) PdM. Traditional PdM usually means the vibration analysis. Traditional PdM (predictive maintenance) using vibration signature analysis is predicated on two basic facts: (1) all common failure modes have distinct vibration frequency components that can be isolated and identified, and (2) the amplitude of each distinct vibration component will remain constant unless the operating dynamics of the machine train change.

The intelligent PdM is big data or AI based intelligent diagnostic algorithms and prediction which the diagnostic efficiency and accuracy are improved significantly.

There are many aspects to collecting meaningful data. Data collection generally is accomplished using microprocessor-based data collection equipment referred to as vibration analyzers.

Diagnostic strategies, emphasizing the importance of predictive maintenance in reducing production shortages and the costs of plant management. The diagnostic strategies include characteristics of condition monitoring systems - data acquisition techniques, data processing methodologies; data compression techniques; alarm levels evaluation (acceptance regions); strategies for detecting fault conditions; diagnostic methodologies for the on-line; expert systems and diagnostic results etc.

2. Chemical Plant Chiller Condition Monitoring and Faults

2.1. Operating history

The chiller (Figure1) is the critical machinery of the chemical plant in BASF Chemicals Company. the chiller unit had been running since 2014, accumulated running hours reached more than 50,000 till 2020 without overhaul.

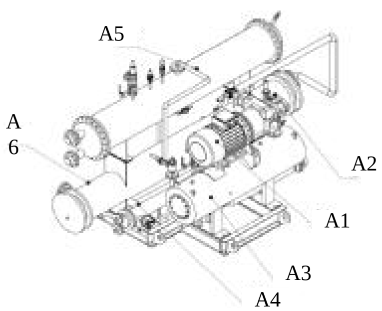

Figure 1. Chiller unit layout diagram

2.2. Chiller unit mechanism

2.2.1. Refrigeration recycles

The compressed high temp. and high-pressure gaseous refrigerant R717 discharges from the compressor (A2) exhaust, through the oil and gas separator (A3), the refrigerant R717 and the lubricant oil are been separated in the oil and gas separator, then enter the coolant system and lubricant oil system to recycle. The high temp. the high-pressure gaseous refrigerant enters the cooler(A5)

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And makes the gaseous refrigerant into the low temp. And low-pressure liquid refrigerant.
liquid refrigerant from the cooler enters the evaporator(A6) after throttling with the throttle valve. The liquid refrigerant evaporates in the evaporator and exchange the heat with the heat transfer liquid, the gaseous refrigerant returns to the compressor inlet for the refrigeration recycle.

2.2.2. Lubricant oil recycles

The separated refrigeration lubricant oil enters the cooler (A4), maintaining the temp. to be stable by the oil temp. Control valve. After the filtering, some of the oil enters the compressor chamber, the others enter the compressor bearings, shaft seals and the balance piston, finally into the compressor chamber for lubrication, sealing, take away some compressed heat. Together with the suction steam, the oil in the compressor chamber are compressed, the high-pressure oil gaseous enter again the oil separator for separating, recycle successively.

2.3. Faults and root causes analysis

2.3.1. Faults statements based on condition monitoring

The predictive maintenance is the monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of machine-trains. the process systems will provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine-train failures. including predictive maintenance in a comprehensive maintenance management program optimizes the availability of process machinery. The predictive maintenance plan Instead of relying on in-plant average-life statistics (i.e., mean-time-to-failure) to schedule maintenance activities, predictive maintenance uses direct monitoring of the mechanical condition, system efficiency, and other indicators to determine the actual mean-time-to-failure or loss of efficiency for each machine-train and system in the plant.

2.3.2. Chiller failures

In 2020 autumn, the chiller unit frequently failed, frequently started and could not run at all on Nov 2020. the unit was running only few minutes then tripped due to high discharge temp (setpoint 90 degrees) and low oil separator level found too in final trial operation in Nov.2020.
Compressor discharge temp too high
Low oil separator level (OIL_LEVEL)
Oil pressure low (ARLARM_40)
Oil temp high

2.3.3. Tradition root cause analysis based on chiller mechanism

HTO (hot transfer oil) outlet temp (T355001) from evaporator exceed high limit (15 degrees).
Too frequently startup, resulting in oil mist together with ammonia could not return to the compressor, low oil separator alarm triggered, oil migrated to evaporator.
The dirty oil filter blocked the oil path.
Oil system dirty due to oil charring from compressor discharge temperature high.

3. Chemical Plant Chiller Intelligent PDM and Diagnostic

3.1. Process diagram and key variables

Reviewed together with the operation, maintenance experts, there are 16 continuous variables of the chiller unit (figure1) are selected to be the inputs for the data mining. It means the trouble shooting with intelligent PdM is based on identified root cause variables. Build the model with all faults, classified to get priority of the importance.

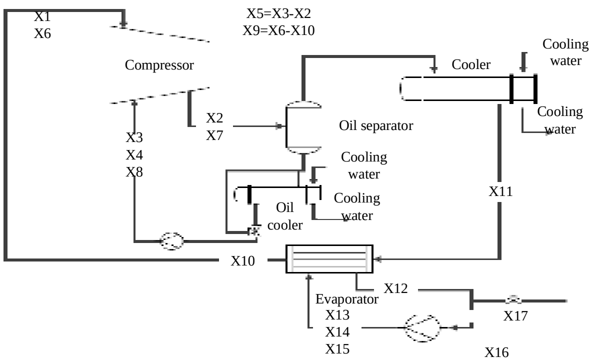

Figure 2. Chiller process diagram

X1: Chiller suction pressure, X2: Chiller suction pressure
X3: Chiller supply oil pressure, X4: Chiller oil filter pressure difference
X5: Chiller oil pressure difference, X6: Chiller suction temp
X7: Chiller discharge temp, X8: Chiller supply oil temp.
X9: Chiller degree of superheat, X10: Chiller vaporizing temp.
X11: Chiller condensation temp, X12: Process fluid 0 degree frozen heat - Conducting oil
X13: 25-degree heat transfer oil return oil control valve open degree, X14: 25-degree heat transfer oil return oil control valve temp
X15:Chiller process fluid frozen heat - conducting oil flow rate
X16: Plant inlet load, X17: Outlet valve open status

3.2. Fault detection

The fault detection is the step in advance. It is used to check if the fault is happened or not. Usually to use normal data to build the model, to calculate the difference between new sample and normal sample online. It is believed there is potential abnormal or fault if the difference between the two is beyond the rational range. The usual way is PCA (principal component analysis), ICA (Independent component analysis), SFA (Characteristics of slow analysis) etc.

Off-line Modeling: use normal data to create KPCA model and calculate T2 and SPE monitoring statistics and their corresponding control limits.

On-line Monitoring: Calculate the monitoring statistics for each new online sample and determine if the value exceeds the control limits.

Below is the Fault Detection Result (Figure 2).

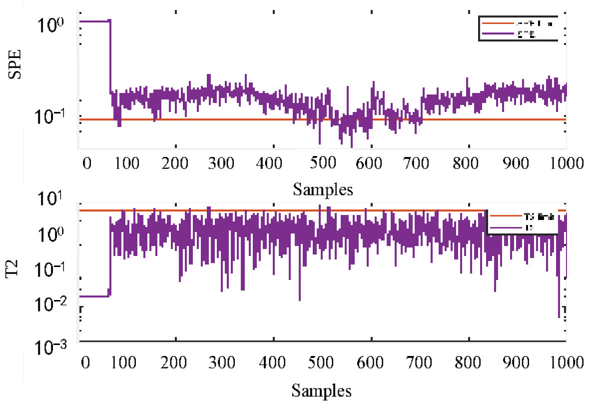

Figure 3. Fault detection result

3.3. Fault isolation

Fault isolation is the measure to pick up the fault variables. When detecting the fault, due to much of process variable numbers and most of the process variables will not be influenced by the fault. Thus, we use the fault isolation to pick up the most influenced variables (fault variables) by the fault. Then the required variables are reduced, and this step usually apply the data after fault to build the model.

Contributor Calculation: After a fault is detected, calculate the contribution of each variable to the exceeded control limit monitoring statistic in the fault sample.

Fault Variable Filtering: Several variables with the highest contribution rate, which are most significantly affected by the fault, are selected, and are called fault variables.

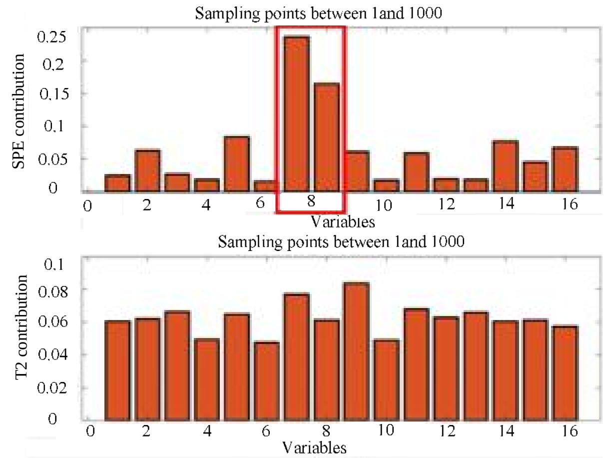

Figure 4. Samplling points between 1 and 100

X7: Chiller discharge temprature

X8: Chiller oil supply temprature

3.4. Root cause diagnosis

The causal inference is performed based on the fault variables from the fault isolation. The root variables are acquired by determining the fault message transfer paths with causal relationships of each fault variables.

Causal Inference: The causal relationship between each pair of failure variables is calculated using Granger causality and transfer entropy methods, and the transfer entropy accuracy is better for nonlinear processes.

Root cause determine: Construct a cause-effect diagram between the fault variables to determine the root causal variable of the fault.

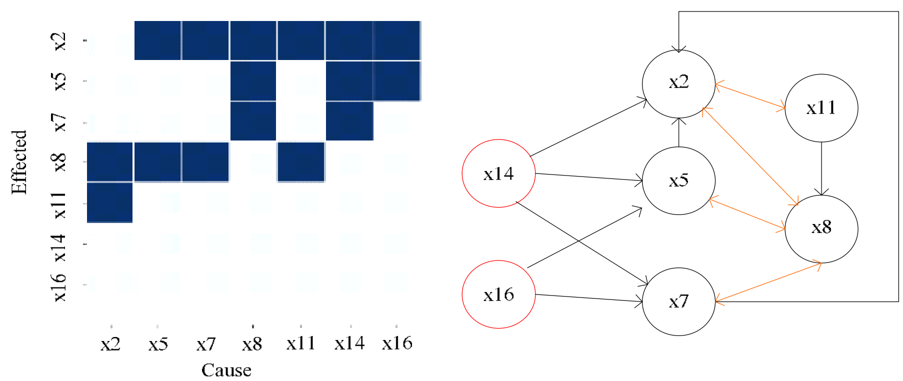

Figure 5. Root cause diagnosis

X14: 25-degree heat transfer oil return oil control valve temp

X16: Plant inlet load

As stated in above, the features importance ranking is achieved. The most important variables are X14, the 25-degree heat transfer oil return oil control valve temperature and X16, the Plant inlet load. And the two variables are confirmed and controlled to improve the chiller system reliability.

Therefore, the bases to achieve the correct root causes are the following. The key fault variables are available and measurable as well as have enough fault data for root cause analysis. Further, need to design dedicated method for different characters (e.g. nonlinearity, non-stationarity etc.) for root causes analysis. Finally, the diagnostic ability can be further improved if use measure points, the connected relationship of adjacent equipment and another tested knowledge.

3.5. Machine learning and pattern recognition

Machine learning generates models that can capture and mimic the behavior of a plant. These models can be used to predict failures and recognize operating modes. It is under working for the algorithms for machine learning such as Neural Networks, Decision Trees, Linear Classifier.

Pattern Recognition, this feature allows the recognition of patterns and regularities in data. It consists, for example, in identifying operating modes by detecting clusters with related data in scatter plots or in discovering recurrent sequences in alarms and events databases. Exploration The exploration step is important to clean the input data set before performing advanced analysis.

These new diagnostic systems would have to cope with the so-called Big Data phenomenon, which will inevitably also have an impact on the development and implementation of the analytical techniques underpinning them.

4. Summary and Path Forward

Together with traditional mechanism analysis, the intelligent PdM can provide a full picture with root causes identification. There are several decision supporting tools for predictive maintenance. These include embedding early anomaly/fault detection, diagnosis, and reasoning, remaining useful life prediction (fault prognostics), as well as optimization, control, and self-healing techniques.

The comprehensive predictive maintenance program can and will provide factual data on the actual mechanical condition of each machine-train and the operating efficiency of each process system. A predictive maintenance program can minimize unscheduled breakdowns of all mechanical equipment in the plant and ensure that repaired equipment is acceptable mechanical condition. The program can also identify machine-train problems before they become serious. Most mechanical problems can be minimized if they are detected and repaired early. Normal mechanical failure modes degrade at a speed directly proportional to their severity. If the problem is detected early, major repairs can usually be prevented. It can provide reliability and operation managers with information that will enable them to achieve optimum reliability and availability from the plans.

Fault diagnostic model has been built for the chiller unit, with the machine learning for real time platform monitoring in future, the system reliability can be improved significantly and guaranteed.

It also can use the reference performance curve to identify performance gaps. The benefit is to reach operational excellence by Detecting abnormal events. Delivering knowledge to operations. Managing performance deviations. Increasing visibility across the enterprise. Abnormal Events Detection allows to monitor and manage day to day plant operations and supply chain performance. It empowers plant manager to make effective business and operation decisions by gathering the right data, information and knowledge scattered across many islands of automation such as distributed control systems (DCS), supervisory controls and data acquisition (SCADA), data validation and reconciliation applications, laboratory information management systems, plant data historians, and enterprise resource planning (ERP).

Empowering Operations with the online model acts as the operations expert by building up knowledge in the system and providing guidance for the operators. It can quickly identify opportunities for operational improvements and root causes of problems when they arise and swiftly guide plant operators in making the most effective decisions. it enables the plant to employ innovative KPI expert functions to monitor and manage plant-wide performance, improve plant safety, and identify areas for profitability improvement. It uses root cause analysis to automatically detect any KPI deviations and advises the plant about their impacts and the proper corrective actions to be taken.

From equipment performance and day-to-day operations to long-term strategic goals, PdM analytics helps the plant to manage the performance and optimize the operations. Diagnostic Analytics transforms real-time data, information, and knowledge into graphical views, thus simplifying and improving visibility at every level of the business hierarchy and generating a global view of the enterprise. The PdM Analytics platform offers a graphical framework that makes applications, such as enterprise asset management and operational performance reporting, easy to integrate.

In such a way, we can pursue the best plant reliability and best process operation optimization.

References

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