CHEMICAL ENGINEERING TRANSACTIONS

VOL. 33, 2013

Guest Editors: Enrico Zio. Piero Baraldi

ISBN 978-88-95608-24-2; **ISSN** 1974-9791

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet

DOI: 10.3303/CET1333039

Rapid Design and Deployment of PHM--A Systematic Approach

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Planning, designing, and implementing a prognostics system requires a systematic approach stemming from business needs to system deployment. Since prognostics make a fit for service assessment of specific assets, the systematic approach begins with a service needs assessment. Given a specific asset or collection of assets, the level of abstraction is defined along with performance metrics. Next, an assessment of data driven, model driven, or hybrid approaches is reviewed to arrive at a prognostic methodology. With the methodology in place, sensors and data acquisition systems form the data acquisition plan. With the data acquisition plan, deployment and experiments are conducted to test and evaluate the prognostic system. Finally, a cost benefit analysis is performed prior to deployment and during testing to determine the solution feasibility, both technically and financially.

1. Introduction

Predictions of process machine state and reliability have been of concern in the chemical applications for many years. For example, Zio et al. (2012) describes the need to predict reliability to aid engineering decision making. The work describes the use neural networks to predict the reliability of diesel engine turbochargers used in chemical applications. Another work of Medina et al. (2011) describes the importance of detecting and predicting degradation of process equipment. Here, the importance of safety as a risk factor coupled with the degradation of the equipment is used to guide equipment inspection strategies. Predictive algorithms including neural networks and support vector machines may also be used in predictive control applications. In the case of semiautogenous mills, prediction of machine state is useful inputs for the control system when optimizing energy consumption (Curilem et al. 2011). A final example of work in predictions of process machine state is the use of a non-linear model of a oil drilling system to predict pore and fracture pressures such that the control system can operate the equipment at desired pressure levels (Vega et al. 2011). Without the adaptive and predictive control, there exists higher risk of formation damage.

In each of these examples, predictions play a role in operations of equipment and scheduling of maintenance activities. While the above works, describe specific algorithms used, there exists an overarching need for reliability and maintenance purposes of a design process for prognostics applications used within chemical industries. Here we introduce a systematic approach to design and implementation of a prognostics system.

The systematic approach to prognostics design and implementation is a seven step process starting with problem formation that includes the goals of the prognostic program. With business impact goals in hand, subsequent steps include a) asset level of abstraction, asset prioritization, and failure mode selection; b) prognostic method selection, either data driven, model based, or a hybrid of the two; c) a data acquisition plan for live monitoring of assets; d) definition of deployment strategy including data acquisition deployment, baseline development, and validation; e) financial feasibility and f) project execution. This paper provides detail on each of the seven steps and concludes with an example in power generation.

Please cite this article as: Johnson P., Lapira E., Siegel D., Lee J., 2013, Rapid design and deployment of phm--a systematic approach, Chemical Engineering Transactions, 33, 229-234 DOI: 10.3303/CET1333039

2. Problem formation

The first step in problem formation is determining the stakeholders and their needs. Typically, there are three classes of stakeholders: the end user of the machinery or asset, the equipment maker or machinery OEM, and the asset maintenance or service provider. Within these three classes of stakeholders, there are specific service need goals which may include machine or asset uptime, prevention of failures by early detection and warning, human and asset productivity improvement, product lifecycle management, maintenance system streamlining, and improved information management.

An end user stakeholder, such as a power generation facility, may prioritize goals in the areas of human productivity improvement, machine uptime, and maintenance system process streamlining. A machinery OEM stakeholder, such as a pump manufacturer, may prioritize goals of product lifecycle management and asset information management. A service provider stakeholder, such as a maintenance service contractor, may prioritize goals of machinery or asset uptime and failure prevention. Even within these three stakeholder groups, goals may vary depending on the individual stakeholder's environment.

Three other terms may be used to describe project scope. These are root cause analysis, condition based maintenance, and prognostics. Root cause analysis is a method used to identify the underlying "root cause" of the problem. Root cause analysis directly relates to failure prevention, by eliminating the root cause of a specific failure. Condition based maintenance focuses on trends and changes in condition or performance indicators. If the condition or performance indicators indicate or trend towards an abnormal condition, some form of maintenance is recommended. The end benefit of condition based maintenance is both productivity improvement and failure prevention, and may streamline some aspects of the maintenance process. Prognostics is the process of predicting (in time) system or system component deviation or degradation from its normal operating condition. Prognostics has an impact on all six benefit areas with productivity and asset uptime often receiving the largest improvement.

The goals of the stakeholder then translate into the goals of the prognostics application. These goals can be translated into measurable results including productivity improvements, mean time between failures (MTBF), maintenance system efficiencies, and so on.

3. Asset level of abstraction

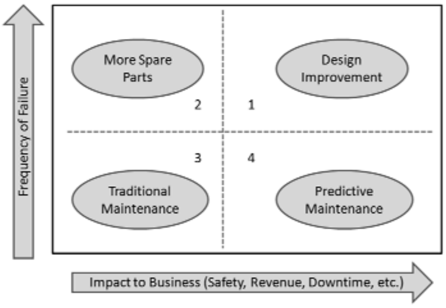
There are four typical system levels to consider in the prognostics design process. These are a) the individual components of a machine or asset, b) the machine or asset itself, c) the process line or plant area, and d) the full system or plant. In the case of a power generation plant, the level of abstraction reaches down to the machine component level including bearings within pumps, motors, and generators. When using the lowest level of abstraction, the component level, it is possible to roll up health indications and predictions to higher levels of abstraction or asset hierarchy.

Within any level of abstraction, there will be several historical failures to consider. By reviewing these historical failures, it is possible to prioritize the assets or components for inclusion in the prognostics design. The prioritization process typically uses a frequency of failure occurrence versus impact to the business chart, Figure 1. Impact may be measured financially, impact to output quality, impact to safety and environment, etc. Within the chart, there are four regions of failures: 1) low impact low frequency, 2) low impact high frequency 3) high impact low frequency, and 4) high impact high frequency. Traditional maintenance or time based maintenance or run to failure often address the low impact low frequency failures. Adding spare parts to plant inventory often address low impact high frequency failures. Prognostics and condition based maintenance address the high impact low frequency failures. For high impact and high frequency failures, a design change to the process, equipment of both is often required. By using this frequency versus impact prioritization technique, it is possible to identify failures best suited for condition monitoring and prognostics.

Once the specific assets and components within the asset have been selected, common failure modes should be identified. A failure mode effects and criticality analysis (FMECA) coupled with historical root cause analysis of historical failures, will lead to specific degradation patterns within the asset or component where the prognostics application should focus.

4. Prognostic method selection

With business goals and assets selected, the next step in the prognostics design and implementation approach is choice of prognostic method(s). The prognostic method and model choice is either a data-driven, model-based, or a combination of the two. The selection process reviews availability of a) physics-based principles of failure b) current material and component conditions c) measureable symptoms, d) and availability of historical data for failure modes.



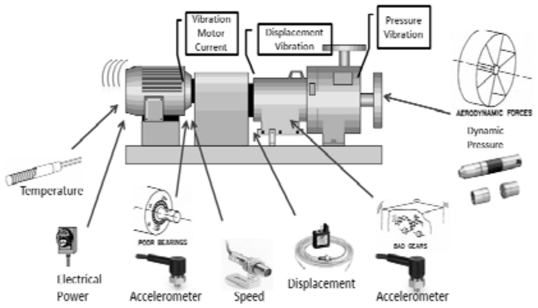


Figure 1: Frequency of failure versus impact *Figure 2: Sample sensors and condition indicating points*

If physics-based failure models are available and measureable symptoms can easily be related to the models, a model-driven prognostics technique may be appropriate. If historical data from measurable symptoms is available and this historical data contains failure modes then data driven prognostics techniques may be appropriate. Also, if material and component conditions are currently normal for the asset, a data-driven technique may also be appropriate. Often, a combination of approaches is desirable. Test cell data from design verification testing or factory acceptance testing can provide normal behavior data sets. Many mechanical components have accepted limits on calculated features such as vibration severity levels for which a simplified model can be inferred. By combining data driven, and macro model driven approaches, a basic automated degradation detection and trending system becomes possible.

5. Data acquisition planning for live monitoring of assets

There are two considerations in the data acquisition planning step. The first consideration is identification of sensor and control system values which provide symptoms of performance and condition degradation. These condition indicating sensors and associated calculations form the parameters used by the prognostics algorithms. The second consideration is complexity level driven by installation needs, data communication, and data storage. Tradeoffs between measurable values and inferred values may be required based on feasibility of installation, communication, and data storage challenges.
There are many sensors available for monitoring and control of machinery assets. Many exist in the machine as a control related sensor, while others are added to the industrial asset for performance or mechanical health indicators, Figure 2. Sensory information reported from the control system may include error codes, torque, cycle step, and so on. These control system parameters are often useful in correlating the machine's work and operating condition with measurements from installed sensors. A third source data is the computerized maintenance management systems or CMMS. The CMMS typically contains information about previous repairs, reported problems, component failures and so on. Data from the CMMS supplements data from the control system and installed sensors adding timing information such as maintenance time windows, costs of repair, causal relations, and so on. Each sensor individually or in combination with other sensors, maintenance data, and analytics provides condition indications which the chosen prognostics methods use to classify and predict developing failure modes.
Each of the possible sensors is matched with expected degradation and failure modes of the asset and asset component. The cost and feasibility of installing or accessing sensors and associated data acquisition systems are assessed. With choice of sensors, feasibility, and cost of data collection in hand it is possible to move to the next step, deployment strategy and experiments.

6. Deployment strategy and experiments

The fifth step in prognostics system design approach includes deployments of sensing and communications components along with experimental validation of sensors and prognostics models. Ideally sensor data, either from installed sensors or from existing data sources, is measured under consistent operating conditions. In the case of a power generation pump, data recordings should be associated with corresponding speeds and loads to separate operating regime conditions from one another. Automatic data recording is preferred over manual collections to enable consistent recording of sensors during each operating regime. The data recording hardware should be connected to the prognostics or systems computing engine, to allow for on-line data feeds with the most up to data sensory data. Finally, feature extraction calculations, such as a Fast Fourier Transform (FFT), should be performed in-line as data arrives. Either embedded or external computing resources can be used for feature extraction calculations.

As sensors and data recording hardware and software are installed, experimental validation techniques are to be organized. Sensor validation determines the ability to measure the condition indicator along with the range of errors. Degradation of the sensor itself should also be considered. In the case of data-driven components of the prognostic strategy, it is desirable to determine and establish baselines for normal conditions as well as any failure conditions. This baseline establishment, or training, creates the basis from which deviations and degradations are measured.

The prognostics models are likely to need tuning and adjustment. For example, principal component analysis (PCA) techniques help isolate those feature calculations from sensor data which are best indicators of degradation towards a specific failure mode. Models may need adjustment to accommodate the adjusted feature inputs. Physics based models in the system may also need tuning to improve the representation of the true behavior of the machine.

6.1 Prognostic testing and validation strategies

Three strategies to consider for validation of sensor and prognostic methods include a) out-of-process health assessment with fixed operating conditions and known failure conditions, b) in-process health assessment with repeating machine operating conditions, and c) in-process adaptive health assessment with dynamic machine operation. Each of these strategies presents challenges and benefits to the prognostics development team.

While the out-of-process health assessment strategy may prove easy to implement and more robust than others, it may interfere with normal operation as the asset is taken off-line for testing. Further, off-line testing provides controlled conditions, thus limiting the ability to detect a broader range of anomalies and degradation patterns. However, it is a well defined program and has relatively low implementation effort from a failure signature development perspective.

In-process health assessment strategies have the advantage of evaluating a full range of in-process degradation drivers. Given the existence of sensors pre-installed in the machinery, this technique may be advantageous in mass production environments with many similar machines. The challenge with in-process repeating operating condition technique is aligning measurements with operating conditions. The effort is slightly higher due to changing operating conditions and the desire to include multiple machines in the validation process.

In-process health assessment is further complicated with operating conditions are dynamic and not repeating on a prescribed schedule. The ability to evaluate in-process degradation drivers is a benefit, while the need to build a larger data set of baselines is a challenge. This technique requires a method to self organize measurements and condition indicators amongst varied operating conditions. The dynamic operating conditions make this validation strategy more difficult.

For balance of plant equipment in power generation plants, operating conditions are most often stable, and not changing. A power generation plant often operates several machines and assets of similar class, make and model. This power generation balance of plant scenario, then is well met with the strategy to perform in-process prognostic validation if needed sensor data is readily available or sensor installation is possible.

7. Prognostic system feasibility and selection

With a deployment and experimental strategy in place, the next step is to organize the prognostics development project with detail to required materials and labor costs. Materials include sensors, cabling, data acquisition platforms, test bed apparatus, and software development tools. Labor costs include installation labor, and software development labor.

Material costs can be calculated with compilation of quotations from sensor and data acquisition hardware vendors. Flexible data acquisition hardware and software will provide greater flexibility to adjust feature extraction and prognostic algorithms as the project develops. Further, industrial grade sensors and data acquisition hardware enable shorter cable runs, thus positively impacting installation labor costs. A software architecture which includes machine level connectivity, sensor fusion, feature extraction from sensor data, prognostics and machine learning algorithms, and dashboard visualization tools will facilitate lower labor costs in software development, Figure 3.

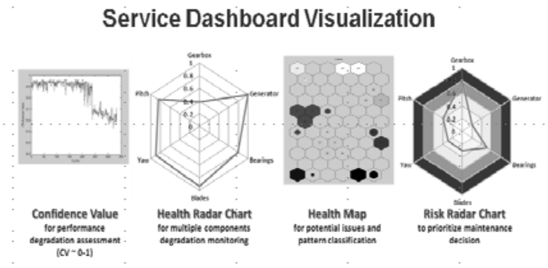


Figure 3: Sample dashboard visualization tools

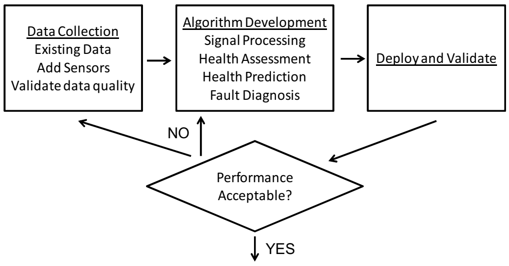


Figure 4: Prognostics project execution process

Labor costs include construction of test beds, installation of sensors and data acquisition hardware, and software development costs. By itemizing these labor categories, the level of expertise to perform the labor and associated costs can be best estimated. Labor costs should also include managing the prognostics system validation process and ongoing adjustments to feature extraction, PCA, and prognostics methods.

With estimated costs in hand, comparison can be made to desired benefits on a financial basis to determine whether the project should move forward. Adjustments to the scope of testing and prognostics system may need adjustment to meet feasibility constraints.

8. Project execution

With the project plan in place, execution can begin. A cycle of data collection, algorithm development and deployment, and validation of results repeats until the performance of the prognostic system is acceptable, Figure 4.

Data collection begins with organization of existing data and baselines. New data is collected from the test cell or from in-process systems. Where feasible, data sets from expected failure modes should be organized and collected. These data sets form the basis for algorithm development and deployment.

Every sensor carries some information indicating the condition of a particular component in the asset or system. A range of signal processing techniques can be used to extract the information or feature from the sensory data. With condition indicators calculated from the sensors, health assessment techniques are deployed to develop degradation patterns and trends. Prediction techniques are used to determine the rate and direction of the trend. Diagnostics techniques are used to identify the liable cause of degradation.

As the prognostic algorithms begin to predict a failure, validation of the prediction should be conducted with asset specific subject matter experts. During the validation process, adjustments to sensors, feature extraction algorithms, prediction algorithms and diagnostics algorithms are made until a consistent and acceptable prognostic system performance is met.

9. Case study: Prognostics systems design and implementation in power generation

In the power generation industry, workforce optimization and uptime of generating equipment are predominant needs of this equipment end user. Two classes of machinery are in use at power generation plants, the turbine generators and balance of plant pumping systems. Turbine generators are highly instrumented as part of the core control systems and are well monitored. However, balance of plant equipment lacks instrumentation. As a result, maintainers of balance of plant equipment spend a lot of time manually gathering and evaluating sensor data from important balance of plant equipment. Hence the scope of this prognostics system is balance of plant pumping equipment with benefit goals of reduction of labor costs for manual efforts coupled with improved uptime and reliability of plant equipment.

Fortunately, sensors and data acquisition equipment costs are more economical today, presenting an opportunity to permanently install sensors and automatic data collection hardware. Using rugged industrial sensors and data acquisition hardware, along with wireless communications, cabling costs are also minimized. Initial sensors include vibration and temperature sensors to monitor degradation in roller element bearings, Figure 5.

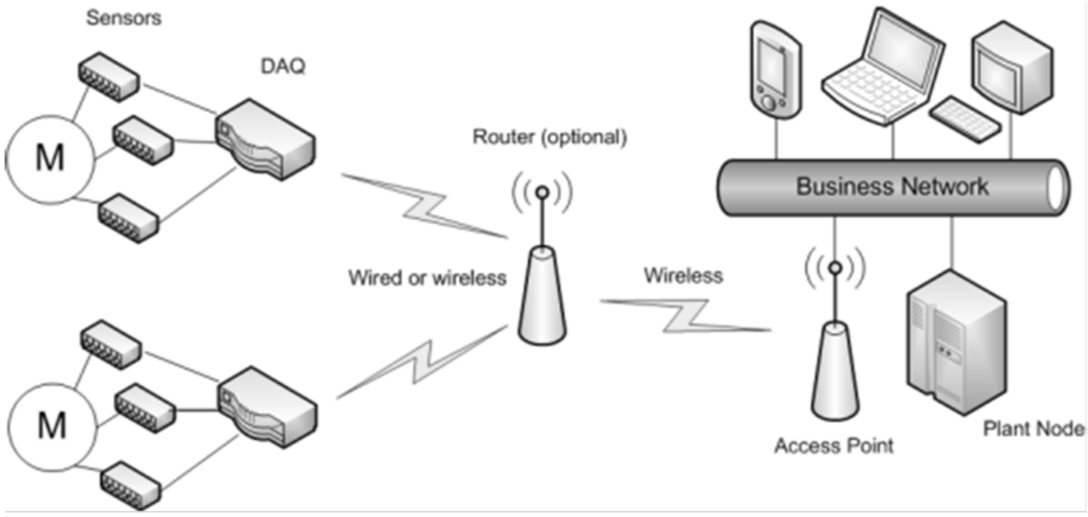


Figure 5: Data acquisition system network for balance of plant pump monitoring and prognostics

Feature extraction from vibration sensors is deployed in the data acquisition hardware. These features indicate the presence of excessive degradation inducing stress. The features are posted to the plant historian where trending and anomaly detection algorithms can analyze features along with supporting plant process parameters. With trending and anomaly detection, plant equipment maintainers can now focus attention on specific equipment identified by anomaly detectors rather than spending time collecting and analyzing data manually. The expected benefit of maintenance worker time optimization is expected to exceed the cost of sensor and data acquisition system deployment.
In 2013, data collection systems are deployed. Feature extraction and anomaly detection algorithm applications are under development and evaluation. Currently, benefits continue to exceed costs, making the power generation balance of plant prognostics project a success in the works.

10. Conclusion

Using the systematic process described here, a prognostic design and implementation project can be evaluated for expected costs and benefits prior to deployment and execution. Given a positive cost benefit analysis, a methodic trial deployment is implemented, adjusted and tuned, and validated for performance of predictions. With lessons learned from the validation process, the prognostics project can be rolled out in a fleet wide manner, expanding the baseline data sets, failure mode signatures, and business benefits to the organization employing the prognostic system.

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