Chapter 4

Typology of condition based maintenance

4.1 Introduction

Industrial maintenance has received significant attention in academic literature for many decades. In recent years industry managers are gradually warming to the idea that maintenance can be a profit generating function rather than merely a cost centre (Alsyouf, 2007). This chapter describes different applications of a particular type of maintenance: condition based maintenance (CBM).

Currently known types of maintenance are shown in figure 4.1 (redrawn after Kothamasu et al. (2006)). In general, maintenance concepts can be divided into unplanned and planned maintenance (Kothamasu et al., 2006; Swanson, 2001). Unplanned maintenance, also called reactive maintenance, is conducted when a failure has occurred and when the original condition is to be restored (i.e. corrective maintenance) or when action is immediately required in order to avoid hazardous situations (i.e. emergency maintenance). Planned maintenance, also called proactive maintenance, can be either preventive or predictive. Kothamasu et al. (2006) identified three types of preventive maintenance: at a constant interval, age based and imperfect. They furthermore mention two types of predictive maintenance: reliability centered maintenance and condition based maintenance. “A condition based maintenance task is performed to detect incipient failures long before their occurrence. Condition based maintenance uses condition monitoring techniques to determine whether a problem exists in equipment, how serious the problem is, and how long the equipment can run before failure; or to detect and identify specific components in the equipment that is degrading (i.e. the failure mode) and to determine the root cause of the problem - the diag-
Figure 4.1. Taxonomy of maintenance concepts (redrawn after Kothamasu et al. (2006)).

Figure 4.2. The 7 modules in the OSA-CBM architecture (based on Lebold et al. (2002)).

nostic function (Mobley, 2002)(cited in Tsang et al. (2006, p.38/39))”. This definition is reflected in the OSA-CBM framework (Lebold et al., 2002) that shows the generic processes inherent in a condition based maintenance application (see figure 4.2). Consequently, an important principle of condition based maintenance is that a P-F curve is known (Moubray, 1997), which indicates a relation between potential failure (P) and functional failure (F). Such curves can be used to estimate the remaining useful life of a piece of equipment and to take appropriate action in time (e.g. prepare a work order and order new spare parts). An example is shown in figure 4.3.

Al-Najjar and Alsyouf (2003), Rosqvist et al. (2009), Waeyenbergh and Pintelon (2004), Waeyenbergh and Pintelon (2009) and Wang et al. (2007) gave some insight into when a certain maintenance technique should be applied. Condition based maintenance and its (potential) advantages were studied (for example Chilcott and Christer, 1991; Jiang and Jardine, 2008; McKone and Weiss, 2002; Swanson, 2001). However, with some exceptions, surprisingly little attention was paid to different aspects and types of condition based maintenance. Jardine et al. (2006) provided an overview of different types of tasks within a condition based maintenance program (i.e. data acquisition, data processing and maintenance decision making) and suitable
models, algorithms and technologies for each task. Kothamasu et al. (2006) presented an explanation of different sorts of maintenance paradigms and their practices. Venkatasubramanian et al. (2003a), Venkatasubramanian et al. (2003b) and Venkatasubramanian et al. (2003c) presented a review of so-called ‘fault detection and diagnosis’ methodologies. Carden and Fanning (2004) conducted a literature review on vibration based condition monitoring. Nandi et al. (2005) examined condition monitoring techniques for electric motors, whereas Han and Song (2003) focused on electrical equipment. In the area of tool condition monitoring, Rehorn et al. (2005) reviewed the most appropriate methods and classify them according to the type of machine operation carried out (e.g. milling, drilling, turning). Although these overview papers help in understanding condition based maintenance and condition monitoring principles, none of them address the question when a certain approach should be utilized and what the characteristics of the underlying dimensions are. It is often said that more classifications in maintenance management are needed (Garg and Deshmukh, 2006). This chapter presents such a classification for condition based maintenance through the development of a typology. The main feature of the typology is that it is grounded in practice and thus offers a good alternative for the (often theoretical) academic approaches to condition based maintenance classifications.

A typology of condition based maintenance is necessary because even though different types of condition based maintenance are applied in practice, little guidance is available for the selection of a certain type. In that sense, literature on condition based maintenance fragmented. The current lack of overview hinders decision making in industry (Koochaki et al., 2008).

Figure 4.3. Component health curves (based on Geraerds (1991); Gits (1992). At \( t_1 \), a signal is given that a fatal situation will occur in the future (at \( t_2' \)). Action will be initiated just before \( t_2' \), at \( t_2 \).
In conclusion, as Waeyenbergh and Pintelon (2009) stated, typologies for effective maintenance decision making are needed. In §4.2 we present the case study, based on which we have developed the typology. Subsequently §4.3 covers the theoretical verification of the typology. Implications are discussed in §4.4. We finish the chapter with conclusions and future research directions in §4.5.

4.2 Case study of condition based maintenance

4.2.1 Background

A multiple case study (i.e. a case study with more than one case, see Yin (2003)) was conducted with the aim to identify specific condition based maintenance approaches and its characteristics, requirements and advantages. Choosing the case study methodology for this purpose seems appropriate since it allows us to obtain an in-depth understanding of the concepts under study. Generally case studies are a good methodology when the study object should be viewed in its natural context (Meredith, 1998; Yin, 2003). Case studies are well-suited when the research objective is considered as theory building (Dul and Hak, 2008; Eisenhardt and Graebner, 2007). The case site is an industrial renovation and maintenance consortium at a major natural gas production facility in The Netherlands. In 1997 the company was awarded the contract to engineer, construct and maintain approximately 25 gas production facilities for about 30 years. Since the gas production plants are all equipped with sophisticated monitoring technology and plant reliability and availability are important factors for the company, it is expected that condition based maintenance would be an important maintenance concept for the company. Thus, the case setting can be considered appropriate for the research objective. At the case company, currently nine condition based maintenance cases are in use.

For the sake of clarity, condition based maintenance is defined in this chapter as the use of monitoring techniques to diagnose or predict failure of a physical artifact, and the activities needed to restore these artifacts into its intended condition. Although this definition is clear, it should be noted here that it needs to be applied loosely. We want to point out that the monitoring of system parameters can be considered condition based maintenance when the purpose of monitoring is to restore system capability through maintenance activities. These activities are preferably known in advance, but it might be possible that they need to be defined after alerting signals are given.
Table 4.1. Current CBM cases at case company.

<table>
<thead>
<tr>
<th>Case Category</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Heat exchanger 1</td>
<td>Temperature residual</td>
</tr>
<tr>
<td>2. Heat exchanger 2</td>
<td>Footprint deviation</td>
</tr>
<tr>
<td>3. Transformer short circuit</td>
<td>Oil analysis</td>
</tr>
<tr>
<td>4. Balancing weights compressor</td>
<td>Vibration analysis</td>
</tr>
<tr>
<td>5. Guard filter</td>
<td>Delta pressure</td>
</tr>
<tr>
<td>6. Seal gas filter</td>
<td>Delta pressure</td>
</tr>
<tr>
<td>7. Lean glycol filter</td>
<td>Delta pressure</td>
</tr>
<tr>
<td>8. Rich glycol filter</td>
<td>Delta pressure</td>
</tr>
<tr>
<td>9. Regeneration time ion exchange unit</td>
<td>Miscellaneous</td>
</tr>
</tbody>
</table>

4.2.2 Research questions and design

We mentioned in the previous section that the current research can be considered theory building. Theory building from case studies is “a research strategy that involves using one or more cases to create theoretical constructs, propositions and/or midrange theory from case-based, empirical evidence (Eisenhardt and Graebner, 2007, p.25)”. The following research questions were developed to support the theory building process:

- What fundamental dimensions distinguish condition based maintenance approaches?
- What characterizes these condition based maintenance approaches?

Since the research objective is the identification of the underlying characteristics of condition based maintenance approaches, the individual cases must be chosen accordingly. As mentioned, nine cases are currently employed at the case company (see table 4.1).

The first two cases concern heat exchangers. One of these cases (labeled heat exchanger 1 in table 4.1) was recently brought into use, whereas the other (heat exchanger 2) is still under construction. Case 3 and 4 are condition based maintenance approaches based on oil analysis of a transformer and vibration analysis of balancing weights. These two cases, however, are under supervision of two major equipment suppliers and are not available for study. Case 5 until 8 all concern pressure differences over filters. The ninth condition based maintenance case is the measurement of the regeneration time of an ion exchange unit. Results were generally considered satisfactorily and over the years, significant experience was built up. We selected two cases for description in the current chapter (cases 1 and 9) since the characteristics of these two approaches were most complementary and typical for the characteristics assumed to be present in the other cases.
Table 4.2. Specifications of the heat exchanger.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive</td>
<td>Anti static V-belts, variable speed drive system</td>
</tr>
<tr>
<td>Material</td>
<td>Duplex stainless steel (tube, header, plug)</td>
</tr>
<tr>
<td>Tube size</td>
<td>Length 13000mm, diameter 32mm</td>
</tr>
<tr>
<td>Electric motors</td>
<td>2 motors (15kW), 1000 r/min</td>
</tr>
<tr>
<td>Fans</td>
<td>2 fans, diameter 3660mm</td>
</tr>
<tr>
<td>Overall weight</td>
<td>65000kg</td>
</tr>
</tbody>
</table>

The first case that is selected concerns a heat exchanger, a largely mechanical item with static components. The monitored condition of the heat exchanger is derived from a process control framework. Although the condition based maintenance approach was chosen carefully, monitoring results led to ambiguous and therefore relatively useless outcomes. The second case concerns the ion-exchange unit used for the demineralization of water (case 9 in table 4.1). Water treatment using these types of ion exchange modules is common in the process industry. Measurement of the condition of the module is expressed relatively simply and the condition based maintenance system for this type of equipment works well. A decrease in the condition of the module is rather a chemical than a mechanical wear process.

Data collection and analysis procedures consisted of interviews, document analysis, and quantitative analysis of ERP-system data and plant information management system data. Case descriptions follow in the next section.

4.2.3 Condition based maintenance case 1 - heat exchanger

Case description
The first case discussed here is the condition monitoring of a heat exchanger (Pot, 2007). Heat exchangers are common, yet critical components in many process plants. The primary function of the heat exchanger in this case is to cool incoming gas from approximately 70 to 26 degrees Celsius. Natural gas flows through a series of tubes with a small diameter cooled by two large air fans powered by a variable speed drive motor. Further specifications are provided in table 4.2.

The heat exchanger is controlled by a model-based controller. Model-based control is nowadays standard in the process industry. The principle is straightforward: a measured output signal is compared with a predicted output signal and based on this comparison a control signal is created with which the process is corrected (in this case through a correction of the fan
speed). For more details about such controllers, see for example, Venkatasubramanian et al. (2003a). In case of the heat exchanger, the actual output temperature (PV) is compared with the predicted temperature (DLAY), resulting in a residual $T_{error}$. Figure 4.4 presents a simplified version of the model-based control of the heat exchanger and its relevant parameters.

Before the residuals data can be presented, it has to be carefully checked and validated. Since the raw data consisted of some noise, a filtering technique was needed. For the heat exchanger, it is determined that only data points that are in a ‘steady state’ are included. In this case, the definition of steady state is based on several filtering rules: minimum gas flow, the operational mode of the heat exchanger, the time interval for selecting data points and the minimum time interval in which data points need to be (relatively) stable. The latter requirement is tested by an intelligent plant-wide filter that is used at the case company as part of a capacity analysis system (also see Veldman et al. (2007)). The determination of a good (string of) data point(s) constitutes a complex task. Figure 4.5 shows the filtered data plot of a heat exchanger at a gas production location along with the estimated (cubic) trend ($R^2 = 0.55; p < 0.001$).

The next step was to establish a relationship between failures and signs of malfunction in the data. This exercise produced some challenges. It appeared that the dominant failures (i.e. internal and external fouling) were not (sufficiently) reflected in the data. The condition parameter did not indicate the most important failure mechanisms appropriately. An analysis and discussion of these findings are postponed to the next section.
Discussion of the results

The case is an example of an application whereby the expected value or trend is obtained through an analytical model and whereby process data are used to monitor the equipment’s condition. The analytical model in this case is the comparison of the predicted value with an actual value: $T_{\text{error}}$ equals PV (i.e. the predicted temperature) minus DLAY (i.e. the expected temperature), where DLAY is a fairly complex function of inlet temperature, gas flow and ambient temperature.

There appear to be three types of potential advantages for using this type of condition based maintenance. The first advantage is that this type of condition based maintenance is based on knowledge of the process, captured in an analytical model. It can therefore provide insight into the actual process and consequences of deviations from the model parameters. Data can be plotted in many ways using different types of filters. When compared to the expected behavior, such knowledge should in theory increase the potential for appropriate decision-making. However, in this case, decision-making remained problematic, since the values of the measured data were not sufficiently influenced by the most important types of failure. This yields an important requirement for this type of condition based maintenance.

The second potential advantage is that this type of condition based maintenance produces many possibilities for analysis. Since a large number of process parameter settings and measurements in the plant are recoded and time-stamped, the condition indicator can be plotted against different parameters and measurements and analyzed subsequently. One such parameter is the state of the plant (start-up, steady-state and shutdown).
The third potential advantage is that this condition based maintenance approach can build on the *use of existing tools*. Instrumentation equipment and ICT-infrastructure were all in place at the gas plant and this condition based maintenance application did not require any major additional investments. However, significant effort was required for accurate filtering of data. Pot (2007) showed that this task should not be underestimated.

Four requirements were identified. The first is a technical requirement, namely that the *process parameter needs to be representative of critical equipment conditions/ failure mechanisms*. This appeared to be a key problem, which was severely underestimated in this case. The residual parameter did indeed measure the deviation of the predicted temperature, but none of the identified failure modes in the FMEA of the heat exchanger could be unambiguously related to apparent deviations. The second requirement is that *sufficient knowledge of the process* (often referred to as the domain of ‘process (control) engineering’) is available to interpret the often complex set of measurements and possible deviations from defined expectations. In the current case, the process and process control engineers appeared to possess sufficient knowledge of the process. However, together with process knowledge, also *knowledge of failure mechanisms and their behavior* (often referred to as the domain of ‘maintenance engineering’) needs to be in place when designing the application, which is the third requirement. Availability of this knowledge was limited in this case, and early theoretical estimations could not be confirmed by actual measurements of the degradation mechanisms.

An important aspect concerned the cooperation between ‘process (control) engineering’ and ‘maintenance engineering’. Process engineers and process control engineers develop and improve industrial processes and its control. Maintenance engineers are typically concerned with detecting failure mechanisms and improving plant reliability through trend analysis and subsequent maintenance concept development. The different emphases of these engineering disciplines appeared to introduce a barrier for the successful implementation of this condition based maintenance case. Although some maintenance engineering experience regarding in- and external fouling was built up in other cases, for example, no historical records for the case under study were available. These findings led to the recognition of the fourth requirement, namely the need for *integration of process engineering and maintenance engineering knowledge* in operating this type of condition based maintenance.
4.2.4 Condition based maintenance case 9 - ion exchange module

Case description
The second case we describe concerns the cooling unit of the compression system of the gas plant. In order to avoid lubrication problems (i.e. possible contamination and environmental risks) and noise, the compressor is equipped with an active magnetic bearing (AMB) system. This system makes sure that the rotating axis remains in a stable position through the application of a strong magnetic field. In order to cool the power-electronics of the AMB-system, demineralized water is used. It is known that the conductivity of the water increases over time. For various reasons, increased conductivity is unwanted. For the demineralization of the water, an ion exchange module is used. If the conductivity of the water is too high (i.e. is above a certain benchmark level), then a bypass valve is opened and the water is sent through the module, which consists of resin. In the module ion exchanges take place, decreasing the conductivity of the water. If the conductivity is below a certain set-point, then the valve is closed. This process is called regeneration.

Over time the functionality of the ion exchange module will decrease (i.e. it will get exhausted). It is important to note that the regeneration process will lengthen with the decreasing condition of the module. Therefore the condition of the module can be expressed as the time it takes for the module to decrease the conductivity of the water from the current level to a target level. This level, along with the maximum and minimum regeneration time, is determined by both the original equipment manufacturer (OEM) and through the use of empirical data. The condition of the resin module is defined as follows:

- The unacceptable condition is a (maximum) regeneration time of 60 minutes. This is the 0% mark.
- The optimal condition is a (minimum) regeneration time of 10 minutes. This value is labeled 100%.

When the data of an ion exchange unit in a single plant is expressed in a time frame of approximately 6 months, the picture presented in figure 4.6 appears.

The graph resembles a near-perfect P-F curve (although the two ‘hiccups’ were left unexplained; according to a maintenance engineer they were the result of data misrecording). The curve can be used for condition based maintenance under the assumption that the regeneration time increases with the amount of regeneration cycles. It is estimated (together with the OEM)
that with every regeneration cycle, the regeneration time increases with 1 second. This implies that with a negotiated plan-time of 60 days and an assumption of 10 cycles a day, a maintenance alert will be given with 600 cycles remaining or a condition of 20% (a 60 day period with 10 cycles per day is 600 cycles in total. Replacement of the ion exchange module should be initiated after the cycle time is increased with 50 minutes, which equals 3000 seconds and thus 3000 cycles. Hence (600/3000)*100%=20%).

Together with the fact that the regenerative capacity is utilized to its maximum, using condition based maintenance for the water system seems justifiable for at least two reasons: (1) production loss is prevented; if the conductivity of the water is above the given maximum, then a shutdown will be necessary, (2) health, safety, environment and well-being (HSEW) risks are reduced since some unnecessary site visits are prevented.

Discussion of the results
In this case, a statistical method is used for obtaining an extrapolation of the measurements, since the approach is merely based on trend data. Unlike the use of the analytical model in the first case, in this case a detailed understanding of the degradation process is not necessary. The data used in the ion exchange module case can be labeled failure data (i.e. singular symptoms of failure, the data are not expressions or dimensions of the process but direct expressions of failure of the module). One can make assumptions about how the ion exchange module degenerates, but for the approximation of this process one can only rely on statistical approximations, which are for a large part based on experimentation of the OEM.

A clear advantage of this type of condition based maintenance is the robustness and simplicity of the approach. It is relatively easy to derive a set of
Typology of condition based maintenance

Table 4.3. Summary of case data.

<table>
<thead>
<tr>
<th>Condition indicator</th>
<th>Case 1 - heat exchanger</th>
<th>Case 9 - ion exchange module</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant failure modes</td>
<td>Temperature residual</td>
<td>Regeneration time</td>
</tr>
<tr>
<td></td>
<td>Fouling; mechanical problems with fans; cracking, breaking, chipping of metal parts</td>
<td>Wear of resin module</td>
</tr>
<tr>
<td>Data management need</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>OEM involvement</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>CBM application success</td>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

data points and interpret the results. The degradation mechanism, however, builds upon an important assumption, namely that the OEM has established the statistical approximations correctly. This might be uncertain, since it is probable that the OEM tested the degeneration process under laboratory conditions or other conditions which may differ from those at the gas production plant (which may vary with the operational settings of the plant, the weather, etc.). This means that there may be important uncertainties in the data and the requirements for data storage and statistical analysis (including sample sizes, control variables and confidence intervals). The requirement is therefore that the statistical data, which are used as a reference, are obtained under similar circumstances as the conditions in which the condition based maintenance case is applied. Naturally, this only goes for relevant circumstances (i.e. circumstances influencing important variables in this case).

This case places no requirements in terms of process engineering knowledge. This type of approaches only requires capabilities in terms of maintenance execution, which means taking the defined action based on the measurements. Table 4.3 presents a short summary of some generic case data. In the following two sections, the results are discussed further and a condition based maintenance typology is proposed.

4.2.5 Result: typology of condition based maintenance

The case studies described here indicate that there are two important denominators for a certain type of condition based maintenance: (1) the method for obtaining the expected value or trend and (2) the type of data used. The method used can be either a statistical or an analytical model; the data used
can be either process data or failure data. The two denominators are important since they represent fundamentally different ways in which one can look at a (system of) physical artifact(s). When a matrix is composed based on these two denominators, four types of condition based maintenance appear, as shown in figure 4.7. The four labels are defined as follows:

- Process data are direct expressions of process dimensions of the system (and indirect expressions of failure). Examples are temperature, flow and pressure.
- Failure data are direct expressions of failure of the system. Examples are vibration data, wear particles data and noise data.
- Analytical models are established or estimated relationships between one or more explanatory variables and explained variables.
- Statistical models are the estimated relationships between one or more explanatory variables and explained variables along with an extrapolation of the data based using probability techniques.

Requirements and advantages considered idiosyncratic to the four types are discussed in the next section. Naturally, we cannot yet propose that these two denominators (and the subsequent matrix) are generally applicable for (all) condition based maintenance cases, based on the cases studies. Such a claim can only be made after study of a sufficiently representative number of condition based maintenance applications, as is done in our subsequent literature review (section 4.3).
4.2.6 Requirements and advantages

The advantages and requirements are derived from the characteristics of the two denominators and the findings of the case studies described here. Type I (analytical modeling - process data) has three identifiable advantages. When an analytical model is used with process data, much insight into the process appears. The user will know accurately what the item in that case is able to do and how it responds to deviations in the model. Since the analytical model always results in absolute context-free values, many analysis possibilities arise. Furthermore, important for many current day plants is that process control equipment is already in place and additional investments are deemed undesirable by plant management due to the high costs incurred. Type I condition based maintenance approaches often depend on existing instrumentation, which is an advantage over other approaches. The requirements for type I can be derived from the nature of the type itself. When measuring a condition indicator other than an indicator that is directly related to failure, it is important to establish a clear relationship between the measurements and types of failure. Process knowledge is necessary to be able to relate output deviations to either normal behavior, change in environmental conditions or failure of the component. This knowledge, however, needs to be complemented with maintenance engineering knowledge - the knowledge of failure mechanisms and their behavior. Without such knowledge, deriving failure from process data solely on the basis of the data itself would be a fruitless activity. What is more, not only the availability of knowledge is sufficient for type I approaches to be successful, but also the integration of those two bodies needs to be established. Such integration is commonly accepted in knowledge management (Grant, 1996). A view on the plant based upon process engineering knowledge yields a good understanding of process behavior, but may lack insight into equipment failure. Consequently, maintenance decisions are hard to make. When maintenance engineering dominates decision making, the maintenance organization runs the risk of faulty decision making, since the effects of process variations are unknown. This integration can be seen as an additional requirement for type I approaches.

Type II approaches (analytical modeling - failure data) are limited to using insight into failure. Since the analytical models used are often in closed form, sound statements on component behavior can be provided. This condition based maintenance approach has two advantages: detailed information and knowledge on failure is provided, and process knowledge is not a prerequisite. The requirement for this type is closely related to these advantages. Sufficient knowledge of the failure mechanisms of the critical components and their behavior is needed. This can be brought in through maintenance engineering.
Type III approaches (statistical modeling - process data) depart from the same requirements as type I approaches. This makes sense, since the approach deals with process data. Process data places many constraints on the limits of the condition based maintenance approach, yet creates many opportunities when used carefully. An additional requirement is a general requirement for statistical analysis. This includes careful sampling, and correct use of the underlying distribution, significance and statistical power issues.

Finally, type IV approaches are the most straightforward of the four types. If implemented properly, they are robust and often very simple. Due to the advantage of simplicity, a requirement is that maintenance execution capability is present. Not much interpretation effort is needed since type IV approaches often build upon the premise that action needs to be taken once certain limits are crossed. More than other types of approaches, type IV requires the presence of good and sufficient failure data. As a matter of fact, this requirement turns out to be a major burden.

The proposed advantages and requirements are presented in table 4.4. The typology is tested against available literature examples of types of condition based maintenance in the next section.

4.3 Literature review on types of condition based maintenance

In theory building research it is common to verify case study outcomes with conflicting and similar literature to increase internal validity and generalizability (Eisenhardt, 1989b). Different types of condition based maintenance approaches are described in literature. We conducted a literature search using three databases (Science Direct, EBSCOhost Research Databases and ISI Web of Knowledge) and a full text search on ‘condition based maintenance’, ‘condition monitoring’ and ‘fault diagnosis’. We pre-selected a large set of articles and describe several typical publications for each condition based maintenance type.

4.3.1 Type I - Analytical modeling and process data

Type I covers the use of an analytical model and process data. Most of the applications in this area are situated in the process industry and have its origin in the area of process control. Gertler and Singer (1990), for example, presented a typical fault-detection and identification (FDI) framework for developing so-called parity equations for the analysis of failures. They use residuals which are orthogonal to certain failures and arrange these into isolable systems. The method described can be extended to multiple failures.
Table 4.4. Advantages and requirements of CBM archetypes.

<table>
<thead>
<tr>
<th>Type</th>
<th>Advantage</th>
<th>Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I) Use of analytical modeling and process data</td>
<td>• Provides insight into the process&lt;br&gt;• Many possibilities for analysis&lt;br&gt;• Possible usage of existing (process control) tools</td>
<td>• Process parameters need to be representative of condition of critical equipment&lt;br&gt;• Sufficient knowledge of the process (i.e. through process control engineering)&lt;br&gt;• Maintenance engineering knowledge&lt;br&gt;• Integration of process control engineering and maintenance engineering</td>
</tr>
<tr>
<td>(II) Use of analytical modeling and failure data</td>
<td>• Provides detailed information and knowledge on the different types of failures&lt;br&gt;• Only failure needs to be understood; not much insight into the process is needed</td>
<td>• Sufficient knowledge of the failure mechanisms of critical components and their behavior (i.e. through knowledge of maintenance engineering)</td>
</tr>
<tr>
<td>(III) Use of statistical modeling and process data</td>
<td>• Widely accepted approach (e.g. statistical process control)&lt;br&gt;• High level of applicability&lt;br&gt;• Methods may be relatively simple to apply</td>
<td>• Process parameters need to be representative of condition of critical equipment&lt;br&gt;• General requirements for statistical analysis&lt;br&gt;• Sufficient knowledge of the process (i.e. through process control engineering)&lt;br&gt;• Maintenance engineering knowledge&lt;br&gt;• Integration of process control engineering and maintenance engineering</td>
</tr>
<tr>
<td>(IV) Use of statistical modeling and failure data</td>
<td>• Approach is robust and relatively simple</td>
<td>• General requirements for statistical analysis&lt;br&gt;• Capabilities for maintenance execution</td>
</tr>
</tbody>
</table>
This study clearly shows the complexity of relating (often mechanical) failures to process data. Juričić et al. (2001) combined the use of parity relations with the parameter estimation technique to monitor an actuator system used for passenger aircraft outflow valves for the control of cabin air pressure.

In the area of railway engineering, García Márquez et al. (2007b) presented a condition monitoring system for an electric point machine. The authors use process data such as voltage to analyze system failures. Recognizing the need for good quality data, several signal filtering concepts were used such as the Kalman filter and smoothing methods. Several failure modes such as maladjustments of drive arms could be detected with the proposed condition based maintenance system. Other examples of type 1 can be found in Bindlish et al. (2003), García Márquez et al. (2003), Li (2002), Maryak et al. (1997) and Nikoukhah (1998).

4.3.2 Type II - Analytical modeling and failure data

Type II entails the use of an analytical model and the use of failure data. Not many studies exist in this area. In the area of punching/blanking of sheet metal, Klingenberg and De Boer (2008) found that the process energy increases sufficiently to be noticeable with small increases in the punch tip radius. They showed that this relationship is consistent for different kinds of materials and claimed that this relationship can be used for condition monitoring. The authors continued with a proposal for a hybrid system consisting of expert systems and artificial neural networks for the modeling of tool wear. In another clear example of wear behavior, Li and Limmer (2000) investigated the development of gear wear and tooth fatigue cracks. With a method that uses linear dynamic modeling on the basis of vibration indices, wear and cracks were found to be identifiable. The authors compare actual values with predicted values to derive a condition indicator. Macin et al. (2003) described one of the most widely used analytical tools in condition based maintenance, namely oil analysis. Generally in oil analyses, wear debris and other forms of contamination are related to different types of equipment wear. The method that is proposed is successfully used as a predictive tool for condition based maintenance. Peng and Kessissoglou (2003) suggested integrating oil and vibration analysis, and conclude that this integration yields better diagnostic results compared to the individual monitoring techniques. Other type II applications can be found in Ko and Kim (2000) and Zou et al. (2000).

4.3.3 Type III - Statistical modeling and process data

Type III covers the use of statistical modeling and process data. Most of the examples in this area have its foundation in SPC and/or control engineering.
Bissessur et al. (1999) described a typical process industry case; the process of papermaking. The authors used the help of process operators to identify 60 process parameters that could have a significant impact of production. With a principal components analysis (PCA), nowadays a popular statistical tool for condition based maintenance, the most important contributors to an (statistically) ‘out of control’ process could be found. Another example of the use of PCA in process monitoring is given by Kano et al. (2001). A range of statistical methods specific to chemical process monitoring is given by Wise and Gallagher (1996). Next to PCA, they pointed at the usefulness of the partial least squares (PLS) technique for the detection (and rating) of faults. Despite the fact that PCA is mostly used in the process industry, applications outside this industry can also be found. Antory (2007) used the method to detect and diagnose air leaks in an automotive diesel engine. Other interesting type III papers are, for example, Isermann (1984), García Márquez et al. (2007a), Norvilas et al. (2000) and Weidl et al. (2005).

4.3.4 Type IV - Statistical modeling and failure data

Type IV covers statistical monitoring and failure data. This is the area in which most of the studies and applications are positioned. They mainly have its origin in reliability engineering. A popular type IV tool is proportional hazards modeling (PHM) (see Jardine et al., 2001; Tsang, 1995). PHM is a multiple regression tool which uses condition monitoring data (such as vibration and oil analysis data but also maintenance events such as replacements) to model a component’s hazard rate of failure. A hazard rate is thereby defined as the instantaneous failure rate at time $t^1$. Jiang and Jardine (2008) combined this technique with other statistical techniques to develop a graphical system to depict a component’s health. PHM was compared with an extension of PCA in a paper by Makis et al. (2006) in the analysis of oil data. They found that PHM outperforms PCA considerably when it comes to failure reduction and the prediction of replacement dates. One important prerequisite of PHM is the availability of historical (failure) data. Recognizing that this is not always the case, Sun et al. (2006) provided an alternative model (called the proportional covariate model). Other noteworthy papers in this area are Dong and He (2007), Sinha (2002), Wang et al. (2007), Xu and Li (2007) and Zhan and Mechefske (2007).

This brief literature review shows that the four types of the proposed

\[ h(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1} \exp \sum_{i=1}^{m} \gamma_i z_i(k) \]

where $h(t)$ is the hazard rate of failure at time $t$, $\frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1}$ is the hazard rate Weibull function, and $\sum_{i=1}^{m} \gamma_i z_i(k)$ is the sum over the covariates and its parameters.

1 The basic regression equation of the PHM is $h(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1} \exp \sum_{i=1}^{m} \gamma_i z_i(k)$ where $h(t)$ is the hazard rate of failure at time $t$, $\frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta - 1}$ is the hazard rate Weibull function, and $\sum_{i=1}^{m} \gamma_i z_i(k)$ is the sum over the covariates and its parameters.
The typology of condition based maintenance types can be clearly recognized in the current condition based maintenance literature. The statistical or analytical modeling decision can be identified in the reviewed literature. Also the decision to use process data or failure data can be recognized in the papers we discussed. It appears that particularly the literature originating in the process industry and process control focus on process data, whereas the body of literature most closely related to reliability engineering has a clear focus on equipment and tool failure data. What was noticed furthermore is that we did not find any articles that could not be related to any of the four condition based maintenance types. This leads us to suggest that the typology can be used in general practice.

4.4 Discussion

Maintenance is an activity with often considerable uncertainty and risk (Pruett and Rinks, 1993). The more maintenance activities can be prevented, the better. Condition based maintenance is a technique that optimizes maintenance time, plant reliability, availability and safety of workers and the environment. Although the typology we develop is derived from two case studies and has been tested only through literature, we believe it can be a practical tool towards effective maintenance management. In particular, in the pre-implementation phase of condition based maintenance it can help maintenance managers to verify the presence of the necessary conditions for the successful use of condition based maintenance. Maintenance managers that have already been using condition based maintenance can use the typology to identify the pitfalls of the different types of condition based maintenance, as well as a tool to explain any potential failure and/or disappointing results of condition based maintenance implementations. We hope our typology can help researchers to conduct more empirical studies on the phenomenon, particularly at the plant level. Condition based maintenance decision-making can be made even more effective if the following two issues are resolved:

- We mentioned the importance of data management. The basic idea is that the more failure data is collected, the better the (analytical or statistical) approximations can be established. It is therefore safe to say that for a high efficacy of the use of type II and IV approaches, failure actually has to occur. The paradox lies in the fact that every condition based maintenance approach aims at preventing failure. In other words, these approaches need the data that represents the phenomena they try to prevent! Resolving the paradox would involve investigating the history of the equipment to identify the data that can be used for modeling purposes. It would also involve an assessment
of the importance of component and/or plant availability. The higher this importance, the less one can afford to use actual failure to increase information and knowledge on failure. Therefore, the use of process data (if available) would then be worthwhile using.

• We also mentioned the relationship between process (control) engineering and maintenance engineering. Surprisingly, the gap that exists in practice between process (control) engineering and maintenance engineering has its equivalent in the academic literature. A great deal of reports relate to what we can call the field of maintenance engineering (e.g. Al-Najjar, 2007; Jiang and Jardine, 2008; Tsang et al., 2006) whereas other publications mainly deal with fault detection and diagnosis, more generally known as failure detection and identification (FDI) (see Kothamasu et al., 2006). The latter body of research mainly represent process engineering knowledge (e.g. Sharif and Grosvenor, 1998; Venkatasubramanian et al., 2003a,b,c). With some exceptions (e.g. Isermann, 1993), little connections between the two areas appear to exist in literature, even though the objectives of the two must be identical: improving equipment reliability through an understanding of the behavior of the asset. Research implications will be discussed in the conclusion of this chapter.

4.5 Conclusions and further research

This report presents a new typology of condition based maintenance along with relevant advantages and requirements. The typology is derived from industrial case studies (based on condition based maintenance practices in a major natural gas facility in The Netherlands). The typology is based on the method for obtaining the expected value or trend (through statistical vs. analytical modeling) and the type of data used (process vs. failure data). Each of the types is analyzed in terms of potential advantages and requirements. A subsequent literature survey reveals that the proposed typology is also applicable for categorization of a large number of descriptions of different types of condition based maintenance found in literature. This leads to the hypothesis that the proposed typology is generally applicable.

The importance of collaboration and integration of two main ‘bodies of knowledge’ relevant for maintenance -process engineering and maintenance engineering- is explained here. A maintenance organization cannot conduct solid maintenance without sufficient knowledge of the failure (i.e. through maintenance engineering) and a good understanding of the process involved. Questions related to bridging the gap would introduce an interesting area of
future research.

The typology can be used for detailed further investigations into types of condition based maintenance. The case studies reported here are conducted in the process industry. In this industry, data and information regarding the process is most often available. Furthermore, at the case site, cooperation between process engineering and maintenance engineering was not hindered by time-related aspects. In many projects, maintenance starts when engineering and production/construction are finished. Integration between process engineering and maintenance would then become difficult due to absence of process engineering. This places particular demands on the handover of technical (engineering) documents to maintenance engineering. Therefore the industry-specific dimensions of condition based maintenance need to be identified and understood.

Other interesting areas for further research can focus on the question how the typology can be used in early engineering phases, and how the typology can aid in the process of selecting maintenance concepts (i.e. the concepts mentioned in figure 4.1).