Condition monitoring for maintenance support

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Abstract: Considerable advancement has been made in computer and information technology that can benefit safety and economy in Operation and Maintenance (O&M). However, before implementing new technology in nuclear power plants there is a need for qualification of methods and related tools. The OECD Halden Reactor Project (HRP) has taken an active role in facilitating implementation of technology advances and in particular application of condition monitoring techniques for maintenance support.
TEMPO [1] is a system based on physical models for thermal performance monitoring and optimization developed at the HRP. The system aims at satisfying information needs associated with condition monitoring, on-line calibration monitoring of plant measurements, process fault detection and diagnosis.
The data-reconciliation [2] method used in TEMPO relies on fitting a simulation of the turbine cycle to the actual plant data. The difference between measurements and calculated values (residuals) are monitored to detect deviations. Each measurement point is assigned an uncertainty. How well the simulation fits to the measurements is compared to the given uncertainty. Traditionally this comparison is directly used to determine if there is a fault in the measurement.
By using a time series analysis of plant data, changes below single point statistical significance can be found. Variations in both individual residuals and the global object function, i.e. the sum of all residuals, are small and their values mostly static. Thus, trending the global object function value is important in order to identify possible faults. Comparing residuals with past behaviour enhances fault detection compared with a statistical analysis of each data point.
An example of fault detection is given from the analysis by TEMPO of data from the Loviisa 2 NPP in Finland.
Keyword: condition monitoring, maintenance support.

1 Introduction

The focus of this paper is the analysis using the data-reconciliation toolbox TEMPO on data obtained from the Loviisa 2 NPP in Finland. Instead of looking at case studies for only a few data sets, data from a whole year has been used for this analysis. This has lead to a better method for fault detection.

The data-reconciliation method used in TEMPO relies on fitting a simulation of the turbine cycle to the actual plant data. Each measurement point is assigned an uncertainty. How well the simulation fits to the measurements is compared to the given uncertainty. Traditionally this comparison is directly used to determine if there is a fault in the measurement. This requires that the uncertainty is a true representation of the random variance of the measured value.
The random variance is difficult to obtain as it includes representivity and modelling inaccuracies. From analysis of real plant data it was found that the measurements showed little random behaviour from one time to another. This leads to the conclusion that a time series analysis of measurement residuals would result in an earlier detection of faults. This method is described in greater detail in this paper.

The analysis of these time series is essential in both validating a model and for the implementation of fault detection routines. The method for fault detection relies on the comparison of the current fit to many previous fits. So reducing the variation of the fit increases the chance of detecting new faults. These considerations for model improvements are discussed in this paper. There is also given an example of a fault detection procedure from the installation of TEMPO at the Loviisa 2 NPP in Finland.

2 Physical modelling method

This section details how a physical model of a thermal cycle can be used for condition monitoring. To use

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physical models a statistical method is required to fit the model to the measurement data, but an understanding of how to build the model is also required. Both these aspects are discussed in this section.

2.1 Flow sheets and data reconciliation

The central assumption in data reconciliation is usually that data are distributed according to the normal (Gaussian) distribution. Maximising the likelihood of a set of estimates for the true values $\tilde{x}_i$ given a set of data x_i^+ yields the following minimisation problem [3]:

$$\min\left(\sum_i \frac{\left(\tilde{x}_i - x_i^{+}\right)^2}{\sigma_i^{+2}}\right)$$

$$subject \quad to \tag{1}$$

$$\mathbf{f}(\hat{\mathbf{x}}) = 0$$

where σ_i^+ is the standard deviation of x_i^+. The plant heat and mass balance and any other relationships that might be included in the model appear in the problem as (non-linear) constraints $\mathbf{f}(\hat{\mathbf{x}})$, by which analytical redundancy is introduced. Note that in general the number of dimensions of $\hat{\mathbf{x}}$ is much larger than the number of measurements.

What emerges from the solution to equation (1) is the plant state most likely to have produced the current set of measurements given their accuracy as expressed in σ_i^+.

The value of the sum in equation (1) is termed the object function where as its statistical likelyhood is termed the goodness-of-fit. This expresses the probability that the deviations from a perfect fit occurred by chance, and is therefore a quantitative measure of the validity of the model.

2.2 Residuals

The objective of data-reconciliation is to fit a physical simulation to measurement data. The difference between fitted values, $\tilde{x}$, and measurement values, x^+, is called the residual, v:

$$v = \tilde{x} - x^+ \tag{2}$$

Given the statistical uncertainty in the measurement values, σ_x^+, the resulting statistical variation in the residual can be determined, σ_v (also written as: sigv). The residual is expected to have statistical distribution with a mean value of zero, $N(0,\sigma_v)$ [2], and is related to the measurement uncertainty by,

$$(\sigma_v)^2 = (\sigma_x^+)^2 - (\tilde{\sigma}_x)^2 \tag{3}$$

Where $\tilde{\sigma}_x$ is the corrected (or reconciled) uncertainty. This enables the definition of a value called the adjustability. This is the amount a measurement uncertainty can be adjusted due to the analytical redundancy present in the model. The adjustability is defined as,

$$a = 1.0 - \frac{\tilde{\sigma}_x}{\sigma_x^+} \tag{4}$$

Where a=1.0 for completely redundant measurements and a=0.0 for non-redundant measurements. The degree of redundancy is an indication of how much information there is about the process properties originating from the other measurements.

2.3 Statistical distribution of residuals

From data provided by Fortum from Loviisa NPP unit 2, Fig. 1 shows the distribution of measurement residuals for a given time point. These measurement residuals have been plotted against the measurement adjustability. This we term a *residual plot*. Plotting against the adjustability helps to spread the data out for visual inspection. It is also useful as measurement residuals with very low adjustability are of lower significance for fault detection, [4].

Each dot represents one measurement. The cumulative probability distributions are shown for the actual data, standard distribution, N(0,1), and a scaled distribution, N(0,0.5).

As can be seen the actual data does not fit the normal standard distribution. A closer fit is obtained for a scaled normal distribution, $N(0,0.5)$.

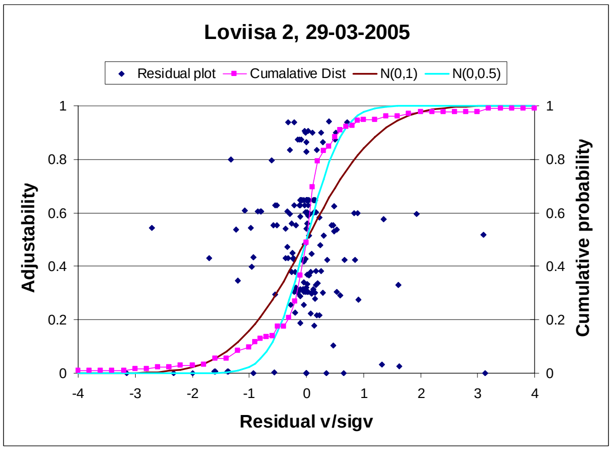

Fig. 1 Residual plot for the 2005-03-29 data point.

The explanation is that the expected normal distribution holds only for an ensemble of instruments, plants and models. For the case considered here there is only one plant, one model and several instruments. In this case the actual data set is a better fit than average, thus the reduced variance of the residual distribution.

It is this understanding that leads to the conclusion that for any individual measurement the majority of the random error in the residual is static as the measurement is always for the same instrument channel, plant and compared to the same model. Thus for a residual trend the variation is much lower than the expected statistical distribution. So it is postulated that errors can be detected by comparing the current measurement residual to its historical values.

2.4 Redundancy

Redundancy means that there is something which is not absolutely necessary. In this case it is applied to measurements. Measurements give information about the process state at a particular point of the process. A redundant measurement can be removed from the system and the process state can still be determined. The different reasons for this redundancy are described below in this section.

2.4.1 Physical redundancy

A measurement is described as physically redundant when there is one or more other measurement at the same point in the process measuring the same physical quantity. As an example this could be two temperature sensors or two flow meters. The requirement that they are at the same point needs some degree of flexibility as there will often be some physical separation between measurements.

2.4.2 Analytical redundancy

Analytical redundancy states that two or more measurements are related by a physical dependency. A simple example is a temperature and pressure sensor at the same location. They measure very different quantities, but if there is wet damp at that process location then they are linked by the dependency of saturation pressure with temperature. In this case there is an analytical redundancy.

The same can be true of two pressure sensors separated by a flow resistance (which can be just the length of a pipe). They will not read the same pressure, but their pressure difference will be a function of the flow properties between them. In this case there is the possibility to link the two pressures with a physical equation.

In general when considering larger systems the relationships between different measurements may be multi-variant and time consuming to analyse analytically. As will be argued in this paper, the analytical redundancy comes from a systematic statistical analysis of the whole system as modelled in a flow sheet.

2.4.3 Apparent redundancy

The final type of redundancy discussed here is that which is introduced through the choice of physical model. These measurements are not truly redundant but appear to be due to approximations made in the modelling. This is a separate type of redundancy as the measurements do not belong to the physical or analytical type.

This arises from approximations made in making the model. An example can be measurements surrounding two parallel heat exchangers. If the heat exchangers are instead modelled as one, which is often done, then some of the physically separate measurements will appear at the same position in the model. Then they will appear to have physical redundancy.

2.5 Modelling equations

One needs to be mindful of which assumptions are made when choosing how to model a system. Different types of equations have different considerations for use.

2.5.1 Fundamental equations

The simplest of models are just based on an assumption that there is conservation of mass and energy. Equations used in these simple models we term fundamental equations. They are always valid and require no tuning of parameters.

2.5.2 Analytical equations

Then there are analytical equations which are derived from fundamental equations but which rely on certain assumed physical characteristics. An example is heat transfer to a smoothly flowing liquid where the flow is assumed to be laminar.

These types of equations are only valid for a range of conditions. In the example above the condition for laminar flow needs to be met. Like the fundamental equations no parameters require tuning.

2.5.3 Empirical equations

Finally there are the empirical equations. Which are derived from experiments an example is the heat transfer in turbulent fluids. The use of these physical equations always carries a certain amount of uncertainty and requires tuning of parameters to the actual system being modelled. They are also only validated for a limited range of physical states. It is this type of physical equation which is most common when modelling the heat cycles of NPPs.

3 Time Series Analysis

As mentioned above the ability to detect system faults is greatly enhanced when the fit of a current time point is compared to the fits of historical values. This we term time series analysis.

In this section we present an example of this analysis from data obtained by using the data-reconciliation toolbox TEMPO with data provided by Loviisa 2 NPP, Finland.

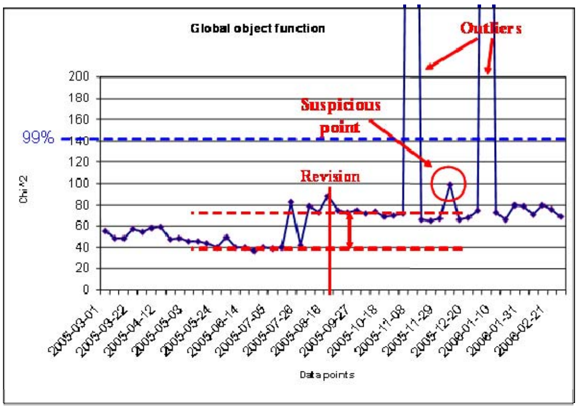

Fig. 2 Time series of global object function, showing limit for 99% statistical confidence limit.

Trending the global object function value, which gives an indication of the ability of the model to fit the data, is important to identify possible faults. Individual residual trends are important to identify and judge the significance of the fault.

Trending the global object function is thus expected to give an overall indication of the state, i.e. if faults are present or not, in the plant. With the heat balance model used in the preliminary study it is expected to mostly detect model or data faults. Fig. 2 shows the calculated global object function value trend for the data set. The variations for fault free data points are low compared to statistical expectation, indicated by the 99% confidence limit also drawn. The faults indicated here are outliers in the data sets, suspicious points (i.e. data sets where the object function value has increased), and changes during the revision period. Here we will discuss the analysis of the suspicions points.

Suspicious points are data points where the global object function deviates from previous behaviour. The data point marked as suspicious in Fig. 2 has a substantially higher object function value than the remaining data set. The increased object function was sustained throughout a five days period.

To identify the cause of the problem, a residual plot for a faulty data point is compared with a residual plot for the previous fault free data point. The two measurements with a significantly increased residual are indicated in Fig 3.

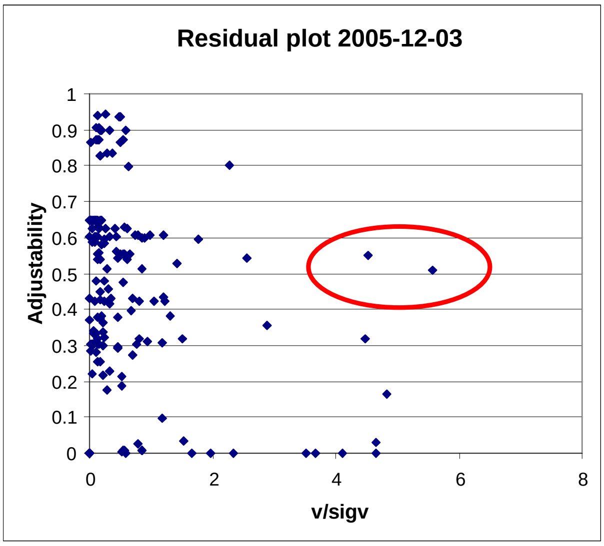

Fig. 3 Residual plot for suspicious data showing measurements whose residuals are significantly different from the previous fault free data.

This fault was then traced to a modelling approximation made in the TEMPO model where parallel condenser units are modelled as a single unit. This is normally a reasonable approximation except for this case described above where there was an asymmetry in the sea water flow to the two condensers. The TEMPO model could be extended to model all condensers individually, should this be desired. However, in normal operation, the condensers are run symmetrically. The extended model would then be unnecessary complex and require more calculation time.

4 Analysis of variances

From the analysis of data from a whole cycle the normal ranges of parameters and deviations can be determined. However it should be noted that the data set cannot be assumed fault free. So any deviations could be due to faults, either measurement, equipment or modelling.
The significance of the variations can be determined by comparing it to the calculated statistical uncertainty. Variations well below the statistical uncertainty are of no significance; whereas variations larger than the statistical uncertainty are.

It is here that the expectations of the different parameter types are discussed. Parameters which should in general vary can be considered as environmental parameters. Examples are cooling water temperature and turbine outlet pressures. Other parameters will be expected to be fixed, such as turbine constants and heat exchanger cleanliness.

These supposed constants are being used in the empirical physical equations. Here their fitted value will only be constant if the correct physical correlation has been used.

This analysis allows for the possibility of fixing parameters, thus moving from a mass and heat balance model to a physical correlation model. Constant parameters can be fixed if their variation is small compared to their statistical uncertainty. Fixing parameters whose variation is large compared to the statistical uncertainty will result in a larger variation of the fit value. This will in turn mask possible faults and is thus undesirable.

The variation in fit (object function) and the values of the empirical equation parameters forms the basis for comparing model improvements. It is not necessary an improvement to reduce the fit value if its variation, or that of an empirical fitting parameter, increases. As fault detection lies in comparing current measurement deviations to historical ones, then reducing the variation in fit value is the most important goal.

5 Fault detection in practice

The data-reconciliation toolbox TEMPO [1,2] is used to analyse one year of data from the Loviisa NPP unit 2. Previously there has been presented analysis of plant data and shown how faults can be detected from inspection of the time series of the key statistical parameters [4]. This method has been used on-line at Loviisa-2 since 2005. The following is a description of an actual fault detected at the plant.

The on-line installation of TEMPO at Loviisa-2 was configured to perform a calculation daily. The global performance indicator was then checked and if its value was greater then 0.95 no further action was taken. This value was set from previous experience of fault free operation.

However, on 20 December its value was found to be 0.68. This prompted further investigation leading to the discovery that the scaled residual values (v/σ_v) showed a significant increase for three measurements. The trend plot of the Q value and one of the residuals is shown in Fig 4.

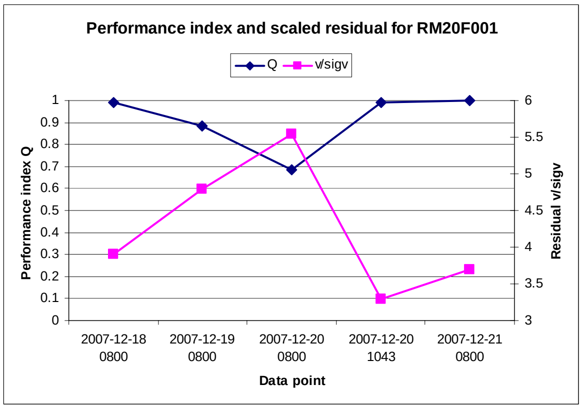

Fig. 4 Fault detection, from goodness of fit key parameter and identification from measurement residual for the main condensate flow.

The measurements concerned are two flows on one of the condensate lines and a steam extraction pressure for the first condensate pre-heater. This led to the conclusion that there was abnormal behaviour in the condensate flow. When the condensate flow was plotted then clear spikes of the flow value could be seen.

The cause of these spikes was later traced to a leaking valve. The leak was only ~0,3 kg/s but it resulted in first filling up the pipe after the valve, and then suddenly draining into the condenser. After flowing into the condenser, this extra water then resulted in an increase in the condensate flow which was spotted as a deviation in the model fit. The reason for this uneven drain flow is unclear. The fault caused a very small lowering of the plant thermal efficiency, and increased pumping requirements. TEMPO is now at Loviisa-2 running hourly to increase the chance of catching such faults.

Physical models provide the plant operator with a lot of new information. The problem then becomes what is the key information to follow and what is the follow up information to examine if a fault is indicated in the key values. In this example the global object function is the key value with the change in the measurement residuals as the follow up information. The choice of key and follow up information is an important factor in the practical implementation of the data-reconciliation technique.

5 Conclusions

This paper has given a brief introduction to the method and application of physical modelling with data reconciliation as applied to thermal heat cycles as NPPs.

This methodology discusses the role of empirical equations in the application of physical modelling methods and stresses the importance of time series analysis as opposed to single point statistical analysis.

With a time series analysis of one year of plant data using the TEMPO toolbox, changes below normal statistical significance were identified. Variations in residuals were small, and their value mostly static. Thus, comparing residuals with past behaviour detects faults earlier than a statistical analysis of each data point.

A systematic method has been developed to enable fault detection and identification based on trending the global objection function as well as measurement residuals. First the global object function value is trended to detect possible faults. Individual residual trends are then used to identify and judge the significance of the fault.

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