

# **Monitoring Nuclear Reactor Thermal Power**

**Strategy of NR power assessment, data reconciliation, validation and instrumentation optimization**

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# **Summary**

- 1. A general approach towards a NR power assessment is described in Chapter 2. The NR power assessment is based on the mass and energy balance of the Nuclear Steam Supply System which can be complemented by the system of the feed water preheat train.
- 2. Chapter 3 deals with mass and heat balancing of steam generators. The assessment of the SG power can be enhanced by data reconciliation and by the inclusion of the phase equilibrium.
- 3. Most of industrial reactor blocks contain several steam generators. The power calculation can be also improved by including the feed water preheat train. Modeling such complex system is described in Chapter 4.
- 4. The precision of the assessed NR power can be improved by the optimization of the instrumentation system (Chapter 5). Two areas of optimization are studied: instrumentation placement and a precision improvement of individual instruments.
- 5. The accuracy of results is composed of the instrumentation precision (influence of random measurement errors) and of the influence of systematic and gross errors. Chapter 6 explores how to protect a NR power monitoring against gross measurement errors.
- 6. In Chapter 7 are explained two main mechanisms of the NR power precision improvement: Data Reconciliation and Streams' Splitting.
- 7. Appendix 1 contains a very brief description of Data Reconciliation
- 8. Appendix 2 describes input data and result files from a part of a real NPP calculated with the aid of the mass and energy balance program RECON
- 9. The report is complemented by an Excel file containing archive of 10 days process data extracted from a PWR NPP (hourly averages). This Excel file can be directly linked as the external data source with the program RECON for automatic data processing (balancing with data reconciliation, gross error detection, viewing trends, etc.) to simulate a real industrial data processing in practice.
- 10.All examples present in this report can be solved with the aid of the Light or the Academic versions of the program RECON, version 11. The automatic data processing of the archive data requires the Professional version of the RECON software.
- 11.Real plant data can be viewed via the Demo example available free at [http://84.242.83.242/pdis\\_web/MainPage.aspx?dst=S&syst=k&schema=index](http://84.242.83.242/pdis_web/MainPage.aspx?dst=S&syst=k&schema=index&user=DEMO) [&user=DEMO](http://84.242.83.242/pdis_web/MainPage.aspx?dst=S&syst=k&schema=index&user=DEMO) (the access password is "demo").

# **1. Introduction**

One of the most important KPIs in Nuclear Power Plants (NPP) is the nuclear reactor thermal power. For electric power generation in NPPs it is typical its low OPEX but very high CAPEX. It is therefore lucrative to run NPPs at the highest achievable power while at the same time the maximum thermal power of industrial nuclear reactors is strictly licensed by authorities. It is therefore very important to know the real NR thermal power (further denoted shortly as *NR* power) with the highest possible accuracy (minimal uncertainty), as this uncertainty of the measured power must be deduced from the licensed power.

There exists no method of a direct measurement of the NR power. All methods available are based on a detailed mass and energy balance of a reactor cooling. This document concerns a pressurized light water reactor (PWR), where the cooling is achieved by a Nuclear Steam Supply System (NSSS). NSSS consists of the reactor, the reactor coolant pumps, steam generators and associated piping. The overall system balanced can include also a feed water preheat train and some other equipment in the primary circuit (containment).

This report has the following structure:

- A general approach towards a NR power assessment is described in the next Chapter 2
- The most important balanced equipment is a steam generator (Chapter 3)
- Most of industrial reactor blocks contain several steam generators. The power calculation can be also improved by including the feed water preheat train. Modeling of such complex system is described in Chapter 4.
- The precision of the assessed NR power can be improved by the optimization of the instrumentation system (Chapter 5)
- The accuracy of a result is composed of the instrumentation precision (influence of random measurement errors) and of the influence of systematic and gross errors. Chapter 6 therefore explores how to protect a NR power monitoring against gross measurement errors.
- Appendix 1 contains a very brief description of Data Reconciliation
- Appendix 2 describes input data and result files from a part of a real NPP calculated with the aid of the mass and energy balance program RECON
- The report is complemented by an Excel file containing 10 days of process data extracted from a PWR NPP (hourly averages). This Excel file can be directly linked as the external data source with the program RECON for automatic data processing (balancing with data reconciliation, gross error detection, viewing trends, etc.) to simulate a real industrial data processing in practice.

Examples solved in this report were calculated by the mass and energy balancing program with data reconciliation and validation RECON [10]. The thermodynamic properties of water and steam are based on the method IAPWS Industrial Formulation 1997 (IAPWS-IF97) [11].

# **2. NR power assessment**

### *2.1. Nuclear Steam Supply System*

NSSS for a PWR consists of the reactor and the reactor coolant pumps, steam generators and further equipment in the containment with associated piping. There exists the ASME document [2] which is the Performance Test Code targeted at procedures for conducting tests to determine the thermal performance of a NSSS including assessment of the NR power. Even if this document is no longer an American National Standard or an ASME approved document, it can serve as a good starting point for a NSSS analysis. Further on in this chapter will be analyzed a hypothetical NPP with one NR and one SG. A more realistic description of a PWR NPP can the reader find in a very good report [17].

A NSSS with one reactor and one steam generator is shown in the next Fig. 2.1:



**Fig. 2.1**: A simple NSSS in a NPP

The most simple is the case of the overall balance of the NR containment, which contains a NR and a steam generator shown in Fig. 2.1. The balance envelope is in the next Fig. 2.2:



**Fig. 2.2**: Balance envelope of the containment

The NR power is denoted here as "energy from fuel". The mass and heat balance around this envelope generates 2 equations (one mass and one energy balance). In [2] the steam flow is supposed to be unmeasured and is calculated from the mass balance (the measurement of a wet steam is problematic). So, the remaining energy balance equation can be used for calculating the directly unmeasurable energy flux from the fuel, which is the NR power.

Inside this balance envelope there can be some measurements on the steam generator. Let's try to use them in the NR monitoring. In the next Fig. 2.3 is a more detailed flowsheet:



**Fig. 2.3**: Detailed balance flowsheet of the containment

There are 3 balance nodes: SGW – water side of a steam generator, SGS – steam side of a steam generator and  $NR$  – the rest of the containment. QNR – thermal power of the NR, EE – sum of the electrical energy inputs (pumps, etc.), QSG – thermal power of the SG, WOUT and WIN – flows of the pressurized water, FW – feed water. Note that such system generates 6 balance equations, but only 5 of them are independent (the mass balance equations around nodes NR and SGW are the same). It is (for example) possible to calculate QNR, QSG, WIN, WOUT and STEAM

streams (without their measurement) or we can have redundancy if some of these streams are measured.

# *2.2. Practical considerations*

Energy loss can't be calculated from the balance as its stream is parallel with the QNR stream. This is a well known result from theory of linear balances. This means that the loss must be determined (estimated) independently on the energy balancing proper (from the containment construction and air conditioning). The overall loss can be considered almost constant as the temperature differences between the equipment and the containment atmosphere is relatively constant.

A major problem in balancing NPPs is that the steam leaving steam generators is somewhat wet. Contrary to classical power stations, this is not only the general problem of the whole Rankine cycle in NPPs (turbines), but also the problem of steam leaving steam generators, as the moisture separation there is never perfect. This fact brings two problems:

- Determination of the steam enthalpy
- Measurement of the steam flow by orifices or similar devices, which are designed for a single-phase flow.

There are several methods of measuring a steam quality (moisture, wetness) which are mentioned in [2] and also in [3], p. 230 – 233. These methods range from a calorimetric measurement to radioactive tracing, but these methods are suitable for specially designed NPP tests, not for the on-line monitoring.

The problem of measuring a wet steam is addressed only in a few papers, for example in [4,16].

In practice it is reasonable to accept values of the steam wetness, measured for example during NPPs acceptance tests, with some reasonably high value of uncertainty for these values.

The Fig. 2.2 does not include additional mass streams entering and leaving the containment balancing envelope. This can be acceptable for sealless main coolant pumps. If this is not the case, also some seal and make up water must be taken into account.

# **3. Steam generators**

This report deals with monitoring of thermal power in a *pressurized light water*  nuclear reactor (PWR). Steam generators (SG) in such nuclear power plant (NPP) convert a hot water into steam from heat generated in the NR core. As there exists no method of a direct measurement of the NR power, the thermal power assessment is based on a detailed mass and energy balance of SGs. In words (see the previous chapter), the NR power can be expressed as:

 $NR power = SG power - Electric Energy inputs + Loss$ , (3-1)

where the SG power (heat flux) is dominant. This is the reason why this chapter is devoted fully to the SG balancing.

SG is usually a vertical or horizontal shell and tube heat exchanger where the hot water flows in tubes and steam is generated in the shell space (recall Fig. 2.1). The important part of the SG is a moisture separator.

## *3.1. SG modeling*

The thermodynamic state at the boiling proper inside the generator can be defined by temperature or pressure. One here assumes phase equilibrium between liquid and vapor phases.

This unit operation can be modeled as a heat exchanger. As the steam generator in a nuclear power plant will be the subject of a more extensive study below, let us now prepare this model for further use.

Heat is supplied to the steam generator (SG) by the high-pressure hot water circulating between the nuclear reactor and the high pressure water part of the SG (SGW). Into the shell part of a SG (SGS) is supplied preheated feed water, the outputs are steam and blowdown (purge) water, which can be both continuous and periodic. The steam always contains a small amount of a liquid phase. The balance model is shown in the next Fig. 3.2:



**Fig. 3.2**: Balancing scheme of a steam generator drawn in RECON

**Note:** While the term *blowdown* is in this case more appropriate the term *purge,* we use in this report systematically the second one because it is shorter.

The feed water stream FW is characterized by its temperature  $t_{FW}$  and pressure  $p_{FW}$ . STEAM and PURGE will be further characterized by the SG temperature *tSGS* and their water contents *X*. PURGE is 100 % saturated water and STEAM is a mixture of a saturated steam and liquid water expressed as % of the wetness (moisture). Hot water is characterized by its pressure  $p_{HW}$  and temperatures  $t_{HWIN}$  and  $t_{HWOUT}$ . The QSG stream represents a heat flux in the SG between the tube and shell spaces (the SG heat power). The model equations are:

SGS mass balance:

 $F_{FW} - F_{STEAM} - F_{PURGE} = 0$  (3-2) SGS energy balance:  $F_{FW} h(t_{FW}, p_{FW}) - F_{STEAM} h(t_{SGS}, X_{STEAM}) - F_{PURGE} h(t_{SGS}, X_{PURGE}) + QSG = 0$  (3-3)

SGW mass balance:  $F_{HWIN} - F_{HWOUT} = 0$  (3-4) SGW energy balance:

### $F_{HWIN} h(t_{HWIN}, p_{HW}) - F_{HWOUT} h(t_{HWOUT}, p_{HW}) - QSG = 0$  (3-5)

In this model, altogether 4 balance equations can be generated (2mass and 2 energy balances). If we measure the flowrates of all mass streams connected with the steam space and the hot water flowrate at the inlet into the high-pressure water space, we have altogether 2 unknown streams, viz. hot water outlet  $F_{HWOUT}$  and the heat flux QSG. If we further measure all temperatures and pressures, two degrees of redundancy are available for reconciliation and data validation. In the case of NRs, sometimes the hot water flow is not measured (insufficient length of tubes ahead of flowmeters in the containment). In this case the degree of redundancy is 1.

### *3.2. SG data reconciliation*

**Example 3.1:** Mass and energy balance of a steam generator

In the following case study we will suppose that the hot water stream input flow is measured.

INPUT DATA:

Besides the mass and heat flowrates, the problem involves 4 temperatures (hot water temperatures HWIN and HWOUT, temperature in the steam generator SG, equal for the outlet steam and purge, and temperature of feed water FW). Further involved are two pressures (FW for feed water and HW for hot water). In addition, we here have two wetness values for liquid water (WATER) and (wet) steam (STEAM).

In the next Table 3.1 is the input data not only for the Example 3.1 but also for other examples concerning the simple SG shown in the Fig. 3.2:

<b>Variable</b>	<b>Stream</b>	Meas.unit	Value	Max.error (uncertainty)
<b>Flow</b>	<b>FW</b>	kg/s	444.5	1%
Flow	<b>STEAM</b>	kg/s	445.0	1%
<b>Flow</b>	<b>BLOWDOWN/PURGE</b>	kg/s	6.12	5%
<b>Flow</b>	<b>HWIN</b>	kg/s	5650	5%
Temperature	<b>FW</b>	$^{\circ}C$	221.6	
Temperature	SGS (STEAM and <b>BLOWDOWN)</b>	$^{\circ}C$	257.6	1
Temperature	<b>HWIN</b>	$^{\circ}C$	295.2	1
Temperature	<b>HWOUT</b>	$^{\circ}C$	265.8	1
Pressure	<b>FW</b>	kPag	4600	0.5%
Pressure	<b>SGS</b>	kPag	4500	0.5%
Pressure	<b>HW</b>	kPag	9600	0.5%
Wetness	<b>STEAM</b>	$\%$	0.25	0.1

**Table 3.1:** Measured variables and their uncertainties

Data were processed by RECON with the following results. The meaning of the individual abbreviations is:



#### **RESULTS**

Task: SG (Balance of steam generator)

Balance: [19.02.2014 23:00; 19.02.2014 24:00)

I T E R A T I O N S



Legend:

Qeq mean residual of equations Qx mean increment of measured variables in iteration Qy mean increment of non-measured variables in iteration Qmin least-square function

#### G L O B A L D A T A



#### S T R E A M S



E N E R G Y S T R E A M S



#### T E M P E R A T U R E S



P R E S S U R E S



#### W E T N E S S E S



Note that the calculated value of QSG is 810 886 kW with the uncertainty 8008 kW  $(0.988\%).$ Additional information:

A sole SG is a very simple model. In the next Table 3.2 is the additional information about DR results:

#### **Table 3.2:** Further results of data reconciliation



Let us further discuss the individual results.

**Adjustability** (see the Appendix 1 and the Section 6.1 for details) gives the relative decrease of a result uncertainty due to the reconciliation. For example for the flow HWIN, this decrease (precision enhancement) is ca by 30 %. Some variables have the adjustability close to zero (almost nonadjustable variables). The latter are those which are measured with high absolute precision (with respect to the other variables); this is for example the case of the PURGE flow. Its relative uncertainty is 5 % but its absolute value small (the absolute uncertainty 0.3 kg/s in comparison with the uncertainty value 4.4 kg/s for the FW).

The further case is represented by temperatures that are also of relatively high precision and in addition are, as steam temperatures, of minor importance in the heat balance. This important fact will be discussed in details also in the Section 5.2 in connection with the optimization of the instrumentation precision optimization. The same holds for pressures which have very small influence on streams' enthalpy.

**Threshold value** (TV, more about it will be in Chapter 6) gives the minimum value of gross error that will be detected with probability Beta. In the Table 3.2 there are

Threshold values for Beta =  $90\%$ ,  $95\%$ , and  $99\%$ . Thus for example the value TV = 795 for the flow HWIN means that the gross error must be at least 795 kg/s so as to be detected with probability 95 % (for information, the flowrate of this stream is 5650 t/h, so the threshold value represents some 14 % of the nominal stream value). It follows from the theory that the threshold value is closely connected with the adjustability of the variable. The smaller the adjustability, the higher is the threshold value (hence also the chance for gross error detection is smaller). Thus for example for almost nonadjustable purges (stream PURGE), the threshold value is several times greater than the nominal one. TVs informs us for which measured variables the gross error detection is efficient and for which measured variables other independent methods must be used (frequent calibration, etc). More about gross error detection will be presented in Chapter 6.

Note that threshold values for pressures are very high. This is typical for almost nonadjustable measured variables. The values presented in the table above just inform us that there is no chance to detect gross errors for such variables (the numbers calculated from the linearized model are not probably completely valid). See also further discussion on this problem in the Chapter 6.

Next result table presents information about parametric sensitivity of the SQ heat power (heat flux QSG).

```
REPORT ON PARAMETRIC SENSITIVITY
 ===================================
Task: SG (Balance of steam generator) ... Balance [19.02.2014 23:00; 19.02.2014 24:00)
Type Variable
 -------------
  HF QSG 
GIVEN VARIABLE IS SENSITIVE TO:
Type Variable Sensitivity Unit
 ---------------------------------------------
 MF FW 1626.592 [KJ/S] / KG/S
 MF HWIN 2.795 [KJ/S] / KG/S
MF PURGE -1458.363 [KJ/S] / KG/S
 MF STEAM 181.093 [KJ/S] / KG/S
 P FW -0.118 [KJ/S] / KPA
 P HW -0.075 [KJ/S] / KPA
 T FW -2013.316 [KJ/S] / C
 T HWIN 566.552 [KJ/S] / C
T HWOUT -509.755 [KJ/S] / C
T SG -180.235 [KJ/S] / C
X STEAM -7224.772 [KJ/S] / %
Legend:
 MF Mass flow<br>P Pressure
    P Pressure
 T Temperature
  X Steam wetness
```
**Parametric sensitivity** gives the sensitivity of the thermal power to the changes of individual variables values. Thus, e.g., the value 1627 for stream FW means that if the measured value of feed water FW increases by 1 kg/s , the thermal power QSG value increases by 1627 kJ/s. More about parametric sensitivity can be found in [1], Section 3.10.

# *3.3. Phase equilibrium in the SG*

The important assumption in modeling steam generators is that the steam and the purge states are on the saturation line. We can then select the temperature or the pressure as the variable from which the stream enthalpies will be calculated (the temperature in the preceding section). If both temperature and pressure are available, we can try to exploit this information for increasing redundancy.

Theoretically it is possible to the Equation (3-3) add the new one written in the term of SG pressure. But this is not enabled in the RECON's GUI. Instead of this we can use the equivalent solution which is based on writing the equation of the phase equilibrium.

Let us now suppose that besides the temperature, also pressure has been measured in the SG. The relation between temperature and pressure is not configured in the graphical editor, but in the editor of user defined equations. There are now two possibilities – either express temperature as function of pressure, or pressure as function of temperature. The result is, however, practically independent of this choice.

**Example 3.2:** Mass and energy balance of a steam generator with a phase equilibrium (compare with the Example 3.1).

In the original model, altogether 4 balance equations were generated, the phase equilibrium assumption generates the fifth. There are two unmeasured variables in the problem, so three degrees of redundancy are at hand for data reconciliation and validation.



**Fig. 3.3:** Editor of user defined equations (demo Example E-11)

Equation EQUIL represents here the relation between measured temperature *T* and equilibrium temperature *T*\*, which is a function of pressure.

 $T^* = T(P)$  (3-6)

In the editor, the equation is of the form

 $[ST < PSG > ]-[T < TSG > ]$  , (3-7)

which is the Eq. (3-6) rewritten with zero right-hand side. Here in sharp brackets <> are the tag names of temperature and pressure variables. Function ST (Saturated Temperature) invoked by button "Saturated steam - temp." has the argument of measured pressure PSG. The second term in the equation is the measured temperature TSG.

INPUT DATA

We will use the input data presented in the Table 3.1. This data will be enriched by the SG pressure PSG (measured value 4 500 MPa with the uncertainty 0.5 %).

#### RESULTS

Task: SG-EQUIL (Balance of SG with phase equilibrium)

I T E R A T I O N S



Legend:

Qeq mean residual of equations Qx mean increment of measured variables in iteration Qy mean increment of non-measured variables in iteration Qmin least-square function

G L O B A L D A T A



S T R E A M S



Note that the calculated value of QSG is 810 912 kW with the uncertainty 8007 kW (0.987 %).

If we will compare this result with the Example 3.1, we can see that there is practically no improvement in the QSG precision.

The major change appears in the following table of adjustabilities and threshold values:

Task: SG-EQUIL (Balance of SG with phase equilibrium) ...

REPORT ON CLASSIFICATION OF VARIABLES

R E D U N D A N T M E A S U R E M E N T S





**Table 3.3:** Adjustabilities and threshold values for Examples 3.1 and 3.2.

The major difference in the Examples 3.1 and 3.2 is in the possibility to validate temperature and pressure in the steam space of the steam generator. For example the gross error of the steam temperature 2.2 °C will be detected with the probability 95 %. These facts will be discussed also in the Chapter 5.

**Note:** If we created a user defined equation for phase equilibrium and temperature or pressure were not measured, this would only serve for computing the unmeasured variable without changing the degree of redundancy. In this case, RECON would only serve as a calculator for equilibrium temperature or pressure. Let us note in addition that in the panel "Node balance", the unmeasured temperatures and/or pressures under phase equilibrium conditions are available for the user automatically, even without defining any user defined equation. ♦

# **4. Industrial NR power monitoring**

The optimal assessment of a real NR power is more complex than the simple system of one NR and one SG presented in the Chapter 2. Modern NPPs has more SGs connected with one NR (typically 4 or 6). The mass and energy balance of such systems can be enhanced (from the point of view of data validation) by incorporating the balance of the feed water preheat system. The high pressure preheat of the feed water is usually well equipped by instrumentation and can increase the data redundancy of the NR power determination.

### *4.1. The feed water preheat train*

Let us consider the scheme given in the following Fig. 4-1a; it represents a two stage system of a feed water preheat.



The deaerated condensate in the Fig. 4.1 a) is pumped from the deaerator (DA) to the deaerated condensate head (DACH). From this point the feed water is pumped to the feed water header FWH1 and then goes to the system of the two stage high pressure preheating system (High Pressure Heaters HPH1 and HPH2), where the feedwater is heated by the extraction steam from the turbine. Finally the feed water

enters the feed water header FWH2. From the FWH2 the FW is distributed to the individual steam generators.

A detailed mass and energy balancing of the whole system is not easy and not essential for the NR power determination. This system contains a lot of unmeasured streams and also the state of the extraction steams is not clear due to their wetness.

In the Fig. 4.1 b) is the reduced balancing scheme. Around the node DACH can be set up only the mass balance as the temperatures around this node are not measured. Around the feed water header FWH can be set up mass and heat balance as all temperatures around this node are measured Altogether 3 balance equations can be generated here: the mass balance around DACH and mass and heat balances around FWH.

## *4.2. NR balancing system*

The reduced balance scheme 4.1 b) can be now incorporated in the system of the steam generation.



**Fig. 4.2:** Feed water preheat and steam generation

We have here 3 measured streams of condensate (INPUT1-3), supplied to condensate head DCH. From here, the condensate is pumped via two measured streams (FWA and FWB) into the feed collector FWHEAD. It is then distributed into 4 steam generators SG1-4. There are further 4 measured streams of purge (PURGE1- 4). In each SG, the measured stream of steam STEAM1-4 is generated. Steam is led into the steam header SH, from where it goes by the measured stream STEAMSUM to the turbine.

Temperatures are measured for all streams of the feed water and steam. The purge temperatures are assumed to be the same as the steam temperatures in the respective SG. The deaerated condensate temperatures are not measured. For this reason, no energy balance around node DCH is created in the model.

Steam generators are connected with the NR by streams of the pressurized water – see the next Fig. 4.3:



**Fig. 4.3:** A nuclear steam supply system with 4 steam generators

One problem is that in our case flows of the circulating water between the NR and SGs are not measured. The mass and heat balance around SGs can only serve for calculation of these unmeasured flows, but this does not increase the redundancy of the system. Therefore we need not include the subsystem of hot water from the nuclear reactor into the balancing system (we can balance only the steam side of SGs and exclude the hot water balance from our system). Let's recall the balancing flowsheet with one steam generator described in the Chapter 2:



**Fig. 4.4:** Detailed balance flowsheet of the containment with one SG

### **Example 4.1:** NSSS with FW preheat

It is possible to merge nodes NR and SGW into one node. The streams of pressurized water then vanishes and the final balancing flowsheet is shown in the next Fig. 4.5, where is the flowsheet drawn in the program RECON



**Fig. 4.5:** Balance schema in program RECON

The heat supply to individual SG is modeled by four heat flows QSG1-4 that come from node NR representing the nuclear reactor. Stream QNR then represents the whole thermal power of the reactor. All losses (LOSS) and electric energy inputs (EE) are concentrated in the NR node. QNR is the key variable to be identified.

Flowrates and temperatures are measured with the following uncertainties:

<b>Type</b>	<b>Stream</b>	<b>Uncertainty</b>
Temperature	All	$1^{\circ}$ C
Flow	<b>STEAM</b>	3%
Flow	<b>PURGE</b>	5 %
Flow	<b>INPUT</b>	1.5%
<b>Flow</b>	<b>FW</b>	1%
Pressure	All	0.5%
Electricity input	EE	2%
<b>Heat loss</b>	<b>LOSS</b>	20 %
Wetness	<b>STEAM</b>	0.1%

**Table 4.1:** Measurement uncertainties

For the majority of nodes, the model creates 2 equations – mass and energy balances. The following nodes make an exception:

- DCH here, the inlet temperatures are not available and only mass balance equation is created
- NR mass flowrates are absent and only energy balance is created.

Altogether, there are 14 equations. There are 5 unmeasured variables (heat fluxes QNR and heat powers of the individual steam generators) in the problem. The degree of redundancy is therefore  $14 - 5 = 9$ .

### *4.3. Main results*

The main results of a typical data set are

Task: NRPOWER4SG (NPP with 4 steam generators)

I T E R A T I O N S



Legend:

Qeq mean residual of equations Qx mean increment of measured variables in iteration Qy mean increment of non-measured variables in iteration Qmin least-square function

G L O B A L D A T A



S T R E A M S



20



#### E N E R G Y S T R E A M S



T E M P E R A T U R E S



P R E S S U R E S



The sum of squares of adjustments *Qmin* = 8.35, critical value of chi-square distribution with 9 degrees of freedom at the significance level 0.05  $[\chi^2$ <sub>0.95</sub> (9)] = 16.90. Since

#### $8.35 < 16.90$ ,

no gross error presence has been detected.

We have found the value of the reactor thermal power *QNR* = 2854 MW with uncertainty 11.2 MW (which represents 0.39 % from the computed value).

### *4.4. Further information*

By its extent, this case study already approaches real problems met with in practice. It will thus be useful to give further interesting results that can be considered typical of this kind of problems.

For the sake of brevity, let us give the results in abridged form. We'll use the fact that our scheme is symmetric around the vertical axis. The values of parallel variables (e.g. parallel stream flowrates) are nearly equal and the same holds for their further properties). So not single results, but only those for the representatives will be given. The results for adjustabilities, threshold values and parametric sensibilities are given in the following table.

REPORT ON CLASSIFICATION OF VARIABLES ===================================== All unmeasured variables observable R E D U N D A N T M E A S U R E M E N T S Type Variable Adjustability Threshold value Unit rnresnoid value<br>Beta: 90% 95% 99% --- MF FW1 0.095917 19.710 21.498 24.799 KG/S MF FWA 0.204919 29.112 31.753 36.629 KG/S MF INPUT1 0.240463 39.933 43.556 50.244 KG/S MF PURGE1 0.000035 25.608 27.931 32.219 KG/S MF STEAM1 0.698680 26.514 28.919 33.360 KG/S MF STEAMSUM 0.876035 105.287 114.838 132.471 KG/S P FW 0.000000 412704.330 450143.298 519264.024 MPAG T FWA 0.184967 3.923 4.279 4.936 C T FWSG1 0.038478 8.274 9.024 10.410 C T SG1 0.024109 10.415 11.359 13.104 C T steamsum 0.552629 2.542 2.772 3.198 C X SGsteam 0.000000 2.273 2.479 2.860 % Legend: Adjustability = relative cut of error due to reconciliation Threshold value = gross error that will be detected with 90% probability MF Mass flow P Pressure T Temperature X Steam wetness

Let us further discuss the individual results.

**Adjustability** gives the decrease of result uncertainty due to the reconciliation. For example at stream INPUT1, this decrease (precision enhancement) is by 24 %. The average value of adjustabilities of all variables is 0.24. This roughly corresponds to the experience from practice, where one gives the result precision enhancement by some 30 % on the average for well instrumented systems. However, one can see here even substantially better adjustability values over 60 %, and also practically nonadjustable variables. The latter are those which are measured with high absolute precision (with respect to the other variables); this is the case of the purges (see also the discussion in the previous case study). Further case is represented by temperatures that are also of relatively high precision and in addition are, as steam

temperatures and the pressure of the FW, of minor importance in the heat balance (also already discussed in the previous Chapter).

**Threshold value** gives minimum value of gross error that will be detected with some probability. Thus for example the value  $TV = 43.6$  for stream INPUT1 means that the gross error must be at least 43.6 t/h so as to be detected with probability 95 % (for information, the flowrates of this stream are ca. 790 t/h, so the threshold value represents some 5 % of the nominal stream value).

It follows from the theory that the threshold value is closely connected with the adjustability of the variable. The smaller the adjustability, the higher is the threshold value (hence also the chance for gross error detection is smaller). Thus for example for almost nonadjustable purges (stream PURGE), the threshold value is many times greater than the nominal one.

### *4.5. Detection and identification of gross errors*

Balancing flowsheets of Chapters 2 and 3 are too simple for showing detection and identification of gross errors (low redundancy). The scheme shown in the Fig. 4.2 contains enough redundancy in this respect. Let us now give two examples from the domain of gross errors detection and identification. We introduce artificially a gross error into our data and our aim is to find it.

Let us begin with an error in the feed water flowrate FW1. According to the report on classification above, the threshold value for this variable is 21.5 t/h. The gross error will be chosen somewhat greater, say 25 t/h. The measured value 370.566 t/h will be increased to 395.566 t/h and the new reconciliation carried out.

During the DR process we get the following message:



NODE:

 <sup>[</sup> SG1 ]



RECON evaluates not only the complex mass & energy balance but also evaluates mass imbalances. Of course, the gross error in FW1 causes significant imbalances in nodes FWH and SG1. This information helps with analyzing the gross errors identification problem.

After the DR process has ended, we have the new result:

 $Q_{min} = 48.9$ ,

which exceeds the critical value  $Q_{\text{crit}}$  = 16.89. So the gross error has been correctly detected. We further apply program RECON menu *Results – Gross errors.* As a result, we have the following message.



It is well known that the variables with great normalized adjustments are candidates for gross errors. We see that the program has found suspected variables and shown correctly the greatest suspect (placed as first, having greatest absolute value of normalized adjustment). There is also a great distance between the first and second variables. We can now continue with the method of elimination of suspect variables from the balance. The suspect variables are one by one put among the unmeasured

ones and the DR process is repeated. The variables with the smallest *Qmin* are then possible candidates. Here is the report on the elimination:

**Results of elimination** 



Legend: Meas. Measured value Calc. Calculated value<br>Diff. Meas. - Calc Meas. – Calc Qmin Sum of least squares Status Qmin/Qcrit (should be < 1

Note that only the elimination of FW1 solves our problem, as the Status is < 1. We can see also that the calculated value of the flow (367) is very close to the measured value (about 368) before the introduction of the gross error.

Now, however, a less favorable situation will be arranged. We introduce a gross error into the flowrate FWA (feed water into feed water collector), of value +35 t/h (the threshold value is here 31.8 t/h, see report on classification of variables above). The measured value 776.776 t/h has thus been increased to 811.776 t/h. After reconciliation, one has found the value *Qmin* = 18.8 , with critical value 16.89 (Status = 1.114). A gross error has thus been again detected. We have further applied again the method for suspect values identification giving the following result.

```
REPORT ON GROSS ERRORS
 ======================
S U S P E C T M E A S U R E M E N T S
Type Variable Norm.adjust. G.e. (abs) G.e. (rel)
 --------------------------------------------------------------
MF FWB -3.647 20.8 3 %
MF FWA -3.638 20.8 3 %
MF STEAM2 2.169 19.3 5 %
MF FW3 1.982 14.4 4 %
Adjustability >= 0.01
Legend:
  Norm.adjust.= normalized adjustment
        (big value \Rightarrow suspect as gross error)
 G.e.(abs) = estimated gross error (absolute value)
 G.e.(rel) = estimated gross error (in % of measured value)
```
In this case, we already have not been that successful as in the preceding one. Now we have two suspects – both streams of the feed water with mutually close values of normalized adjustment. These two suspects cannot be further distinguished by the method used.

Even the application of the suspect measurements elimination method brings no breakthrough:



Again, the elimination of any of the couple FWA and FWB is successful.

The impossibility of distinguishing the two streams follows from the fact that in the scheme, the streams are parallel and in the balance of the two nodes DCH and FWH, they make themselves equally valid. In the case of a linear mass balance only, the two parallel streams should have exactly the same normalized adjustment. In our case the situation is a little bit distorted by the existence of the nonlinear energy balance. The root of these problems is in the covariance matrix of adjustments. If two or more variables have their covariances equal to 1 or -1, they are deterministically correlated and are indistinguishable from the point of view of a gross error identification. However, problems can be encountered also in the cases of covariance close to 1 or -1.

In practice, more cases of similar (although not so obvious) situations can occur. One then often doesn't deal with one error only. As a consequence, the results of gross errors identification are not always unambiguous. Only another independent method could be applied (judging whether the increase in flow over the current limit is possible at all, or scrutinize the measurement system for the two streams).

## *4.6. System without FW preheat*

### **Example 4.2:** NSSS without FW preheat

For completeness, further is presented the NSSS without the FW preheat. It is roughly the balancing envelope of the containment. See the next Fig. 4.6:



**Fig. 4.6**: NSSS without the FW preheat

Results of DR with this system follows (abridged). The degree of redundancy is 6. The QNR value is 2861 MW with uncertainty 14.2 MW (0.50 %).

### These results will be also discussed in the Chapter 7.

Task: NRPOWER4SG WITHOUT PREHEAT (NPP with 4 steam generators without FW preheat)

G L O B A L D A T A



#### S T R E A M S



#### E N E R G Y S T R E A M S



#### T E M P E R A T U R E S



P R E S S U R E S



#### W E T N E S S E S



### *4.7. Complete model with hot water streams*

For completeness, in the next Fig. 4.7 is the complete model of the NSSS which includes circulation of hot water between NR and steam generators.



**Fig. 4.7:** A complete model of NSSS including hot water circulation

Note that steam generators now consist of two nodes – SGS\* (steam water side) and SGW\* (hot water side). All temperatures around steam generators are measured but all hot water flows are unmeasured. There are 8 more equations generated (mass and heat balances around SGW\* nodes. As there are 8 new unknown variables (flows of hot water streams), the degree of redundancy remains equal to 9. This model enables one to calculate hot water circulation which is valuable in monitoring of the whole NSSS. It is clear that the final results (reconciled and calculated values) and all related information (uncertainties, gross error detection possibilities etc.) must be the same a in the case of the simplified model described in the Section 4.2.

# **5. NR power assessment optimization**

There exists a vast literature about optimization of measurement systems, especially about selecting measuring points, see for example [8]. Some of the methods proposed are very sophisticated and powerful. Further on we will try to exploit the relative simplicity of our problem for finding some rules of thumbs in this area by a common sense.

There are several levels on which NR power measurement system can be optimized. Here we will mention two of them:

- Selection of measured variables from the set of all measurable variables. This variant is sometimes called the "instrumentation placement"
- Optimization of instrumentation precision and accuracy.

### *5.1. Instrumentation placement*

Let's start with the steam generator model presented in the Chapter 3. Now we'll describe in more detail the complex processing of data measured on one steam generator of a nuclear power station. Besides the balance proper and data reconciliation, we'll also give further information that can be deduced from the measured data.



**Fig. 5.1:** Steam generator

Hot water (HW) circulates between the nuclear reactor and tube space denoted as SGW. Steam (containing 0.25 % wetness) is generated in the shell space SGS. From the shell space of SG, the purge is continuously withdrawn. The heat stream QSG represents the heat flux (thermal power) in SG. The following table gives measured values and their uncertainties.



**Table 5.1:** Measured variables and their uncertainties

This basic variant of SG was already solved in the Chapter 3. We'll give below further results and analyses.

One of the important measurement results is the heat flux QSG, which plays the main role in the nuclear reactor thermal power identification. One speaks then of a *key variable* of the whole measurement. Usually, there are several different ways for its identification, based on the choice of measured variables and the measured values processing – it is so-called *strategy of measurement* and measured data processing.

Let us further review several variants, in order to show the importance of the strategy for measured data analysis. We here make use of the RECON program.

The individual variants (strategies) of the heat flux QSG identification follows.

- 1. From the mass and heat balances of hot water (balance around node SGW): One deals with direct calculation without data reconciliation on the nuclear reactor side. Data about SGS are ignored.
- 2. From the mass and heat balance of the steam part of the SG: One deals with direct calculation without data reconciliation on the steam generator side. Steam flowrate is considered unmeasured and it is calculated from the feed water and purge flowrates.
- 3. From reconciled mass and heat balances for the steam part of SG: Hot water balance is not taken into account.
- 4. From the reconciled balance of the whole system (model applied in the previous section).
- 5. Strategy No. 4 is made still more perfect on applying new pressure measurement in (the steam part of) SG, and this pressure is reconciled with the temperature in SG according to the phase equilibrium condition.

These strategies can be described by the following *instrumentation placement matrix*:



**Table 5.2:** Matrix of instrumentation placement

Here on the top of the table are the individual variants of the instrumentation placement. 1/0 means whether the individual variables are measured or not.

The results of the QSG assessment uncertainty are in the following table.

<b>Strategy No</b>	QSG [MW]	<b>Uncertainty</b> [MW]	<b>Uncertainty</b> [%]	Degree of redundancy
	868.7	60.5	7.0	
	808.6	8.49	1.05	
	809.8	8.08	0.98	
	810.9	8.01	0.99	
	810.9	8.01	0.99	

**Tab. 5.3:** Identification of flowrate QSG in different ways

The results are in good agreement with simple rules familiar to those which deal systematically with process measurement.

- The choice of the whole measurement strategy is of fundamental importance. Even if strategy No.1 looks very good as concerns the simplicity of the balance calculation, the result is not good. The hot water balance suffers from the fact that it is based on the evaluation of temperature difference of the hot water streams, which is a difference of two large numbers. In addition, there is a relatively great uncertainty of the hot water flowrate measurement.
- Considerably better is the result of strategy No.2 based on the SG steam side balance. The balance works with a relatively precise knowledge of the feed water flowrate. The measurement of temperatures has only marginal importance for setting up the heat balance. This strategy based on simple mass balance is often used in practice.
- Strategy No.3 is supported by the reconciliation of the mass balance around the SG steam side. Further, the result uncertainty is somewhat reduced. In addition, we here have the effect of data validation consisting in the possibility of gross errors detection.
- Strategy No. 4 does not bring any relevant diminishing of the result uncertainty. Two models (No.1 and 3) have been integrated and the degree of redundancy increased by 1. The model according to strategy No.1 brings itself, from the standpoint of thermal power identification, substantially less than model No.3. We here have an asset in enhancing the precision of flowrate measurement on the hot water circuit. More detailed analysis shows that the hot water flowrate uncertainty is lowered by ca. 30 % due to the reconciliation.
- Strategy No. 5 further increases the degree of redundancy, however without any sensible effect on the QSG uncertainty. One deals with reconciliation and temperature precision enhancement, and as shown above, the temperature of steam in SG is of minor importance for setting-up the energy balance. Still, the chance for the validation of temperature and pressure data in SG is then generally better (see the Section 3.4).

Differences of QSG uncertainties among strategies 2 – 5 are not very significant. This coheres with supposed uncertainties of FW and STEAM flows (1 % versus 3 %). For equal uncertainties of FW and STEAM the uncertainty of QSQ for strategy No. 2 would be higher by several tens of percent than for strategies 3 - 5.

### *5.2. Optimization of instrumentation precision and accuracy*

Let's continue with the steam generator balance. In the following example we'll deal with the propagation of measurement errors during data processing. The final target is to use this information for optimization of the instrumentation precision and maintenance.

Information in this respect is provided by the *vector of shares* introduced in [1], Section 3.9 *Propagation of errors at data processing and....* . Let us recall that this vector contains percentage shares of individual measured variables on the dispersion of the result. The program RECON offers the vector of shares in menu *calculations – Propagation of errors*.

Let us further concentrate on the thermal power of SG – variable QSG introduced in the Chapter 3.

Task: SG (Balance of steam generator) REPORT ABOUT PROPAGATION OF ERRORS Type Variable ------------- HF QSG THE VARIANCE OF GIVEN VARIABLE IS CAUSED MAINLY BY: Type Variable Share ----------------------------------- MF FW 82 % MF STEAM 9 % T FW 6 % Sum 97 % Legend: MF Mass flow T Temperature

This list contains only variables with shares greater than 1 %. One can see that the dominant effect on the thermal power precision is due to the flowrates, and in particular those of feed water and steam constituting 91 % of the variance of the result. If we want to make the QSG still more precise, this would make sense just with these two variables. The others are of rather negligible impact. The other finding is that we can improve the QSG precision significantly by including the other FW measurements outside the containment balancing envelope presented in the Chapter 4.

Let us further put the question, why further variables make themselves less valid in the vector of shares. For instance, for the purge measurement, this measurement itself is (absolutely) very precise. While for the feed water measurement, absolute uncertainty is 4.4 kg/s (1 % of 444.5 kg/s), it is only 0.3 kg/s for the purge. For the hot water flowrate measurement, the reason is more complicated. The hot water balance suffers from the fact that it is based on the evaluation of a temperature difference, which is the difference of two large numbers.

Somewhat surprising is the small importance of measured temperatures. Why for example, in the list of relevant variables doesn't occur the temperature in SG, which determines the steam enthalpy, thus the main carrier of energy? One of the reasons is certainly the fact that the assumed uncertainty 1 °C is relatively small and possible impact on the energy balance is not great in these limits. More essential is however the fact that in the temperature domain typical for SG, the temperature dependency of saturated steam enthalpy is flat. This is shown in the next Fig. 5.4:



**Fig 5.4**: Specific enthalpy of the saturated steam and the water [kJ/kg]

The curve of the specific enthalpy in dependence of temperature reaches its maximum somewhere around 235 °C (it is clear that at the maximum the temperature has no influence on the enthalpy). Then the enthalpy falls with the raising temperature. For example at 257 °C the change of the specific enthalpy is ca. - 0.4 kJ/(kg deg C), which is only 0.02 % of the evaporation heat at this temperature.

For instance an error in steam temperature 10 °C (hence ten times the assumed uncertainty) results only in a several tenths per cent error in the stream enthalpy, thus substantially smaller than the flowrate measurement error. With a little bit of exaggeration we can say that for the purpose of balancing in this case the temperature inside the steam generator needn't be measured at all.

Somewhat different is the situation of the feed water. Its specific heat at pressure 4.6 MPa and 220 °C is ca. 4.6 kJ/(kg °C), which is about 10 times more than it was with the steam. Therefore, the feed water temperature occurs in the vector of shares (though still as an item of smaller importance).

For the same reason, in the vector of shares absent is the hot water pressure. The pressure dependency of liquid water enthalpy is even less pronounced than in the preceding case of saturated steam, so that even large errors at the water pressure measurement do not cause large errors in the balance. On the other side however, the chances for the detection of these errors are also bad.

Let's now apply this approach to the more complex system of NSSS with 4 SGs and the FW preheat train solved in the Chapter 4. The result of the propagation of errors analysis follows:

**Task: NRPOWER4SG (NPP with 4 steam generators) REPORT ABOUT PROPAGATION OF ERRORS Type Variable ------------- HF QNR THE VARIANCE OF GIVEN VARIABLE IS CAUSED MAINLY BY: Type Variable Share ----------------------------------- MF FW1 MF FW2** 12 %<br> **MF FW3** 12 % **MF FW3**<br> **MF FW4**<br> **MF FWA**<br> **MF FWA**<br> **MF** FWA<br> **12** % **MF FW4 12 % MF FWA 12 % MF FWB 12 % MF INPUT1 5 % MF INPUT3 5 % MF INPUT1** 5 %<br> **MF INPUT3** 5 %<br> **X** SGsteam 5 % **Sum 86 % Legend: MF Mass flow X Steam wetness**

Here we can see that on the list of important measured variables are only flows, especially flows of the feed water. The only exception is the pseudomeasurement of the steam wetness.

We can deduce that the most important for the precise assessment of the NR power is the exact mass balance of steam generators, especially the exact assessment of the FW input.

We can conclude this section with the observation, that there is a class of important variables which should be properly measured and their instruments should be regularly maintained and calibrated. In warranted cases we should think about replacement of the existing instrumentation by a better one (with a lower uncertainty and greater reliability).

# **6. Protection of NR monitoring against gross errors**

One of major benefits of Data Reconciliation and Validation is the possibility to protect monitoring systems of industrial Key Process Indicators against malfunctions of measurement systems and similar problems. This Chapter is the abridged version of the paper [12].

In essence, there are at least three major benefits of data reconciliation (DR):

- 1. Reconciled data are consistent with the model
- 2. Reconciled data are more precise than data directly measured
- 3. DR represents a solid basis for detection, identification and elimination of data corrupted by gross errors.

While the first two benefits need not too much discussion, the remaining one deserves a comment. Even if this benefit is often denoted in the literature as "invaluable", the exact knowledge of strength of the DR method is quite scarce. This chapter will concentrate on evaluation of the last benefit in practice.

### *6.1. Precision of reconciled data*

The precision of data can be characterized by their covariance matrices *F*. Between covariance matrices of *x +* , *x'* and *v* holds the following relation [1]

$$
F = F_{x'} + F_v \tag{6-1}
$$

The precision of individual variables (elements of vectors) is characterized by their standard deviations  $\sigma_i$ , which are square roots of diagonal elements of respective covariance matrices

$$
\sigma_i^2 = F_{ii} \tag{6-2}
$$

As  $\sigma_{V}^{2} \ge 0$ , the following inequality holds

 $\sigma_i \geq \sigma_{x'i}$  (6-3)

saying that there can be some improvement in precision due to DR. This improvement can be characterized for the *i-*th variable by the so-called *adjustability ai*

$$
a_i = 1 - \sigma_{\mathsf{x}} / \sigma_i \tag{6-4}
$$

The adjustability of any measured variable represents the reduction of its imprecision caused by DR. As will be seen later, adjustabilities are remarkable variables having importance also in area of gross error detection. From the definition follows that any adjustability lies in the interval <0 ;1):

- value 0 represents the so-called *just determined variable,* which is not influenced by DR and is not adjusted at all (*nonredundant* variable)
- value in the interval (0;1) means *redundant variables* which are adjusted in the process of DR

Further it is supposed that covariance matrices of reconciled values *x'* and of estimated values of unmeasured variables *y'* are available (the already mentioned DR Engine) and thus providing uncertainties (confidence intervals) of reconciled values.

### *6.2. Gross measurement errors*

Let's modify Equation (A1-5) in the Appendix 1 to the form

$$
x^+ = x + e + d \quad , \tag{6-5}
$$

where *d* is a gross error (which is a constant). The most simple and frequently used method for detection of gross errors is the well known chi-square test [1,5,6,7,8,9] applied to  $Q_{min}$  defined by Eq. (A1-3).  $Q_{min}$  has the chi-square distribution with  $V$ degrees of freedom. A gross error is detected when the following inequality holds:

$$
Q_{min} > \chi^2_{1-\alpha}(v) \tag{6-6}
$$

where  $\chi^2$ <sub>1- $\alpha$ </sub> (*v*) is the critical value of the  $\chi^2$  distribution with v degrees of freedom and the confidence level  $\alpha$  (0.05 in our case).

### *6.3. Power of the 2 test*

As every statistical test, also the  $\chi^2$  test has its power characteristics shown in Fig. 6.1.



**Fig. 6.1**: Power characteristic of the  $\chi$ 2 test

On the *x*-axis there is the magnitude of a gross error. On the *y*-axis is the probability *P* that the gross error will be detected. The power characteristic for a measured variable equals the confidence level  $\alpha$  in the absence of the gross error ( $d=0$ ) and approaches 1 for high values of the gross error  $(d \rightarrow \infty)$ . *TV* is the value of a gross error which will be detected with probability  $\beta$  ( $\beta$  = 0.95 further in this paper).  $TV_{\beta}$  is characteristic for every measured variable. The lower is  $TV<sub>\beta</sub>$ , the better. It is clear that gross errors can be detected only for redundant measured variables.

Threshold values can be calculated from equation

$$
q_i = \delta_\beta(v,\alpha) / [a_i(2-a_i)]^{1/2} \tag{6-7}
$$

where  $q_i$  is a dimensionless threshold value  $TV/\sigma$ , which means

$$
q_i = TV_i/\sigma_i \tag{6-8}
$$

and  $\delta_{\beta}(v,\alpha)$  is a constant characteristic for the confidence level of the *chi*-square test  $\alpha$ , number of degrees of freedom  $\nu$  and the probability that a gross error will be detected  $\beta$ .

Equation (6-7) is slightly re-arranged equation (4.143) from literature [5]. Values of  $\delta_{\beta}(v,\alpha)$  are not available in standard statistical tables. Details about calculating threshold values and constants  $\delta$  (for  $\alpha$ =0.05,  $\beta$ =0.9 and  $\nu$  = 1,2, ..., 20) can be found in literature [1]. In this paper will be used the new equation (6-9) for the more convenient  $\beta$ =0.95. This equation approximates  $\delta$  (for  $\alpha$ =0.05) in the range of  $v = 1,2$ , … ,400).

 $\delta_{0.95}(v, 0.95)$  = 3.59399 + 0.471951 ln( $v$ )+ 0.014197 ln( $v$ )<sup>2</sup> + 0.015074 ln( $v$ )<sup>3</sup> (6-9)

It is worth mentioning that threshold values are simple functions of adjustabilities defined by Eq. (6-4), see also the next graphical presentation of Eq. (6-9).





Some simple conclusions can be deduced from this graph:

- the higher is the adjustability, the higher is the probability to detect a gross error (low value of the threshold value)
- for adjustabilities less than 0.1 the chance for detecting gross errors diminishes steeply

### *6.4. Target variables and their protection against gross errors*

In practice, there always exist one or several variables, which are of key importance. They are the main reason why hundreds of other variables are measured, collected and processed. The measurement target can be for example a nuclear reactor heat output while errors can be hidden in measured flows and state variables of steam and water. The basic question is: "How are these target variables protected against gross errors of the measurement?"

We are successful if **A**: "A gross error is present and eliminated while maintaining an accurate value for the target variable." We are unsuccessful if **B**: "A gross error is present but not identified and an inaccurate value for the target variable is determined."

In analogy with statistics (power of statistical tests) we can define the probability of an event **A** as a power of the Monitoring System Self-Protection (MSSP).

Let's further suppose that for a target variable *h*, we know (require) the *maximum acceptable error ehmax*. This tolerance can be consumed by

- 1. a random error *ehr* caused by random errors of all measured variables (further we suppose Gaussian errors with Normal distribution). As the random errors are not known, we will substitute *ehr* by *ehrmax* which represents the *tolerance* of *h* caused by random errors (the information provided by the DR Engine).
- 2. a constant gross error *ehg* caused by a gross error of one measured variable *d*  in the sense of Eq. (6-5)

We require that

$$
e_{hmax} > e_{hrmax} + e_{hg} \tag{6-10}
$$

Inequality (6-10) sets the upper limit on the error *ehg* caused by the gross error, further denoted as *ehgmax*

$$
e_{hgmax} = e_{hmax} - e_{hrmax}
$$
 (6-11)

This means that both errors' tolerances add to form the overall tolerance. The situation is illustrated in the next Fig. 6.3.



**Fig. 6.3**: The overall tolerance ehmax consumed by random and systematic errors

It is clear that the *reserve* should be non-negative to satisfy our MSSP requirement (6-10).

The MSSP analysis will be based on a combination of two methods:

- gross error detection power described in the previous paragraph
- a parametric sensitivity of the target variable with respect to the individual measured variables.

Let's suppose that a target variable *h* is a function of measured variables in the sense of Eq. (A1-7).

$$
h = h(\mathbf{x}^*)
$$
 (6-12)

In this case the function *h()* represents the whole DR process starting by collection of measured values and ending by calculations of target values.

A parametric sensitivity  $\zeta_i$  of  $h()$  with respect to a measured variable  $x_i$  is defined as the partial derivative

$$
\zeta_i = \partial h(\mathbf{x}^*)/\partial \mathbf{x}^* \tag{6-13}
$$

The process consists of two steps, which are applied to all measured adjustable variables:

- 1. determination of the threshold value for the *i*-th measured variable
- 2. evaluation of the parametric sensitivity of the target variable with respect to the *i*-th measured variable.

The process is illustrated in the next Fig. 6.4, which is a continuation of Fig. 6.1. On the right hand side y axis there are errors of the target variable caused by a gross error of the *i*-th adjustable measured variable.



**Fig 6.4**: Power characteristics (full curve) and the parametric sensitivity (dashed straight line) for the i-th measured variable (the index i is omitted here for brevity)

It is supposed that the function (6-12) can be linearized and that a gross error of the *i*-th measured variable transforms to the error of the target variable according to Eq. (6-13)

$$
e_{hg} = \zeta_i d_i \tag{6-14}
$$

This equation is represented by the dashed straight line in Fig. 6.4. There are two important points on the x axis:

- 1. threshold value  $TV<sub>\beta</sub>$  which informs that gross error was detected (with probability  $\beta$ )
- 2. critical value of the gross error *dcrit* . At this point *ehg* reaches the maximum value *ehgmax* and exhausts all tolerance available (point **A** in the Fig. 6.4).

$$
e_{hgmax} = \left| \zeta_i \right| d_{\text{crit},i} \tag{6-15}
$$

or

 $d_{\text{crit},i} = e_{\text{hqmax}}/|\zeta_i|$  (6-16)

Now it is time to compare the power characteristic curve with the parametric sensitivity straight line. The most important is the relation between *dcrit,i* and *TV,i* . If there holds the inequality

$$
d_{\text{crit},i} > TV_{\beta,i} \quad , \tag{6-17}
$$

the gross error will be detected before causing unacceptable error in the target variable and the system is well protected against a gross error of the respective measured variable (this case is depicted in Fig. 6.4). In the opposite case an undetected gross error can devalue the target value significantly before it is detected. The inequality (6-17) can be expressed also in the alternative way by substitution of *dcrit,i* from (6-16) to (6-17):

$$
e_{hgmax} > |\zeta_i| T V_{\beta,i}
$$
 (6-18)

saying that

#### *The product of the parametric sensitivity and the threshold value should be*  less than the tolerance belonging to the gross error set a priori for the target *variable.*

The inequality (6-18) thus represents the only criterion for assessing whether the target variable is self protected by DR (and the following data analysis steps) against gross error(s) in the *i*-th measured variable. The inequality (6-18) must be checked for all measured variables.

### *6.5. Example: Nuclear Reactor heat power monitoring*

The heat released in the nuclear reactor is not directly measurable, it is calculated from the mass and heat balance of the feed water and the steam generation systems.

The following example is a simplified version of the 1000 MWe PWR Nuclear Reactor (NR) heat balance problem described in the Chapter 4. The heat loss and the electricity consumption are for brevity neglected.

*QNR* is the **target variable** to be determined. The model generates 14 mass and heat balance equations among 28 measured variables and 5 unmeasured variables (heat fluxes QSG and QNR). The mass and enthalpy balances were set up around all nodes excluding the INPUT, where only the mass balance was used. The degree of redundancy is therefore  $14 - 5 = 9$ . There are 9 degrees of redundancy available for DR and gross error detection.

Let's analyse the possibility to protect such system against gross measurement errors. **It is required that the overall error of** *QNR* **should not exceed 1.2 % of the nominal value, which is 3000 MW, i.e. 36 MW**.



**Fig. 6.5**: The balancing flowsheet for the example

Flows and temperatures were measured with the following tolerances (maximum errors):





The major results of data reconciliation were:

*Qmin* = 14.4

(the critical value  $\chi^2$ <sub>0.95</sub> (9) = 16.9, hence no gross error was detected). The calculated NR heat power

 $QNR = 2820.7 \pm 10.8$  MW,

therefore the tolerance of *QNR* belonging to random errors *ehrmax* equals 10.8 MW (0.38% of the calculated value).

As the maximum allowed tolerance is 36 MW, the undetected gross error should not cause greater error in *QNR* than  $36 - 10.8 = 25.2$  MW (according to Eq. 6-11).

Results of the analysis are summarized in the next Table 6.2. As the flowsheet is symmetrical, results will be presented only for the representatives of parallel streams (for example conclusions for all 4 STEAM streams are almost the same).



**Table 6.2**: Analysis of MSSP for the Example. TV = Threshold Value (the critical value of TV  $\vert \zeta \vert$  is 25.2)

\* values after installation of the measurement of the sum of purges

The values in the last column are now compared with the limiting value, which is 25.2 MW according to the Inequality (6-18). From the Table 6.2 follows that the target variable *QNR* is quite well protected against gross errors for most of measured variables as they pass the Inequality (6-18). The only exceptions are the PURGE streams.

Really, any of the purge streams has very low adjustability (and therefore relatively high threshold value) and at the same time also high parametric sensitivity. The value from the last column of Table 6.2 is 44.2 MW which is almost twice the allowed tolerance for QNR (25.2 MW). This means that the system is not protected against gross errors in purge flow measurements.

Let's try to raise the redundancy of the instrumentation system. The redundancy of the purge streams is very low (they are checked only by the balance of steam generators, while feed waters and steam has its own redundant balancing subflowsheets). By adding the measurement of the sum of all purge streams (tolerance 5 % of the measured value), the problem is completely solved.



**Fig. 6.6**: The balancing flowsheet after adding the purge sum measurement

After this step the threshold values of all purge streams fell from 29.1 to 2.2 kg/s. The result is presented in the last row of Tab. 6.2. It can be seen that the adjustability of purges increased by more than two orders after the installation of the new measurement.

### *6.6. Interpretation of results and conclusions*

Results of the Example can be interpreted in the following way. For the whole system we can conclude that it is (after installing the new measurement of the sum of purges) well self-protected against gross errors as concerns the target variable *QNR*  and its required tolerance. Especially

*The probability that any undetected gross error will impair the required tolerance of QNR (36 MW) is less than 5 %, provided that the measurement of the sum of purges is installed.*

Otherwise the flowmeters of purges must be checked independently of the data validation and reconciliation procedure described above. Such interpretation can help in deciding which measured variables are self-protected by DR and which need independent checking, calibration or additional redundancy.

Let's briefly discuss some limitations of the proposed method. The solution is based on linearization of the nonlinear model. This is a general problem of the DR technology. It depends on how far from the point of the solution the linearization is applied. In our problem we should look how big the threshold values are, as applied in inequality (6-18). In practice, if the threshold values are up to 10 % of the flow or

up to 10 centigrade in the case of temperatures, the errors introduced by linearization are small and smaller than the other errors (model errors, estimation of measurement precision, etc.). If the threshold values are bigger, it is possible to use the Monte Carlo simulation to check whether the linear model works well.

Conclusions drawn from the method proposed should be applied in the statistical sense. This means that they are valid for a large number of data sets, for example in the case of a continuous monitoring of an industrial process. Benefits of DR are of a statistical nature.

The proposed MSSP analysis is based on the assumption that only a single gross error may exist in the system. This should be the case of a well maintained monitoring system where the probability of multiple gross errors is low. In the case of simultaneous gross errors the problem starts to be more complex (not only for gross error detection but also for their localization).

The method proposed is quite simple and can be useful in the process of analysis of existing monitoring systems. It **makes possible to find which couples of target variables and measured variables are automatically protected** against gross error and which primary measurement needs independent checking or frequent calibration. This work can be also useful in the optimization of the instrumentation placement as was shown on example of measurement of the overall purge.

# **7. Discussion and conclusions**

Some results were already discussed in the individual chapters. Here we will look at the overall problem of the QNR assessment uncertainty.

Let's recall 3 Cases in this report:

- 1. Assessment of the 1 SG power (QSG) in the Example 3.1. This is not the case of the full QNR assessment but very close to this problem (see the Equation  $(3-1)$ ).
- 2. QNR of the 4 SGs without the feed water preheat train in the Example 4.2.
- 3. QNR of the 4 SGs with the feed water preheat train in the Example 4.1.

The uncertainties of measured variables are the same for all Cases. The most important results of these cases – thermal power uncertainties - are summarized in the next Table 7.1:

Case	<b>Variable</b>	Degrees of redundancy	Uncertainty (%)
	<b>QSG</b>		0.99
	QNR		0.50
	QNR		0.39

**Table 7.1:** Uncertainties of QSG and QNR in per cents of the power value

Note that the uncertainty falls with the raising degree of redundancy which is in tune with the theory. A question is whether the uncertainty in the Case 3 is not too much optimistic? The uncertainty value of the QNR 0.39 % is substantially smaller than that of any of the measured flows. Moreover, also errors at setting-up the heat balance should play a role. Let's analyze this problem in details.

There are 2 major effects which must be taken into account.

- Precision improvement due to data reconciliation
- Precision improvement due to steam's splitting.

Further on in this chapter will be for simplicity supposed that

- The flowmeters used have the same relative uncertainty expressed in per cents, irrespective of the flow
- The random errors of flowmeters are uncorrelated
- This is the problem of the (linear) mass balance only.

In the next Fig. 7.1 there are two simple flowsheets illustrating this problem:



**Fig. 7.1**: Data reconciliation and stream's splitting

In the Fig. 7.1a) is the case of 4 flowmeters placed on one line (streams  $S1 - S4$ ). Such system can be reconciled. There are 4 streams and 3 nodes. The degree of redundancy is 3. Let's suppose that the nominal flow in this system is 100 kg/s and its uncertainty is 10 % (10 kg/s). After the data reconciliation in the program RECON, the all reconciled values have the uncertainty 5 kg/s. This means that the DR cut the uncertainty by 50 %.

This simple example resembles the flowsheet in the Example 4.1. The FW streams are measured on 3 levels, the steam on two levels, similarly as in the Fig. 7.1a).

The next influence was probably not presented in the literature on industrial data processing. Imagine again that the overall flow in this system is 100 kg/s and the uncertainty of flowmeters available is 10 % (10 kg/s). There is the possibility to split this stream into the four same parts  $(S1 - S4)$ , each flow 25 kg/s with the uncertainty 10 % (2.5 kg/s) see the Fig. 7.1b). The stream S5 is not measured but calculated from the balance as the sum of four streams. The final uncertainty of such calculated stream S5 in the program RECON is then again 5 kg/s, the same as in the preceding case of the DR. This benefit of 50 % precision improvement is not due to the DR but due the law of errors propagation during the S5 calculation:

 $S5 = S1 + S2 + S3 + S4$  (7-1)

To explain it in words, when measuring the same thing (the flow of the S5 stream) by several instruments, the positive and negative errors can cancel in some extent.

This example also resembles the flowsheet in the Example 4.1. The FW and STEAM streams are measured on 3, 2, 4 and 4 parallel streams, this also enhances the final QNR uncertainty.

These two simple examples have shown that the precision improvement is enabled by two different mechanisms of the relatively same power, by DR and by stream's splitting.

**Note:** the cut of the uncertainty by 50 % in both cases is only incidental and holds only for this number of streams.

## **References**

- [1] Madron, F., Veverka, V., Hošťálek, M.: Process data validation in practice. Applications from chemical, oil, mineral and power industries. Report CPT 229-07. Usti nad Labem 2007 [Online] [http://www.chemplant.cz/CPT\\_229-](http://www.chemplant.cz/CPT_229-07_Process%20Data%20Validation%20in%20Practice.pdf) 07 Process%20Data%20Validation%20in%20Practice.pdf
- [2] ASME PTC 32.1-1969(R1992): Nuclear Steam Supply Systems
- [3] Cotton, K.C. Evaulating and Improving Steam Turbine Performance Monitoring. Cotton Fact Inc., Rexford, NY 1998.
- [4] Crowe, C.T., Weiss, H.: Metering Low Quality Steam-Water Flows. UCRL-52271, Lawrence Livermore Laboratory, Livermore, CA 1977
- [5] Madron F., Process Plant Performance. Measurement and data processing for optimization and retrofits. Ellis Horwood New York, 1992
- [6] Romagnoli, J.A., M. C. Sanchez, Data Processing and Reconciliation for Chemical Process Operations, Academic Press London, 2000
- [7] Narasimhan, S., C. Jordache: Data Reconciliation & Gross Error Detection. An Intelligent Use of Process Data, Gulf Publishing Company Houston, 2000
- [8] Bagajewicz, M.J.: Process Plant Instrumentation: Design and Upgrade. Technomic, Lancaster 2001
- [9] Knopf, F.C.: Modeling, Analysis and Optimization of Process and Energy Systems. John Wiley & Sons. Hoboken, NJ 2012
- [10] RECON Mass, heat and momentum balancing software with data reconciliation.<http://www.chemplant.cz/recon.asp>
- [11] IAPWS Industrial Formulation 1997 for the Thermodynamic Properties of Water and Steam. International Association for the Properties of Water and Steam. ASME PRESS, NY 1998
- [12] Madron, F, Hostalek, M, Stepan, L: Protection of a Nuclear Reactor Monitoring System against Gross Measurement Errors. International Journal of Nuclear Energy Science and Engineering (IJNESE) Volume 5, 2015
- [13] NUREG/CR-6895, Volume 1. Prepared by J.W. Hines, R. Seibert and S.A. Arndt. Technical Review of On-Line Monitoring Techniques for Performance Assessment. Division of Engineering Technology, Office of Nuclear Regulatory Research, U.S. Nuclear Regulatory Commission Washington, DC 20555-0001. January 2006
- [14] Gay, R.R., Palmer, C.A., Erbes, M.R. Power Plant Performance Monitoring. New Delhi : Tech Books International, 2006.
- [15] Veverka, V: Balancing and Data reconciliation Minibook, [ONLINE] <http://www.chemplant.cz/download.asp>
- [16] Morita, R. at all: Clarification of Measurement Error of Orifice Flow Meter in Wet Steam Flow, Paper No. POWER2011-55457, http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?articleid=1 629655
- [17] The Westinghouse pressurized water reactor nuclear power plant, Westinghouse Electric Corporation. Water Reactor Divisions. Pittsburgh, Pennsylvania 15230, 1984 [on line] http://www4.ncsu.edu/~doster/NE405/Manuals/PWR\_Manual.pdf

# **List of abbreviations**



# **List of symbols**

- *a* adjustability (6-4)
- *d* gross error (6-5)
- *dcrit* gross error causing error of a target variable equal to *ehgmax* (Fig. 6-4)
- *e* random error with Normal (Gauss) distribution (A1-5)
- *e<sup>h</sup>* error of a target variable *h*
- *ehmax* maximum allowed error of a target variable
- *ehgmax* maximum allowed error of a target variable due to a gross error
- $\vec{e}_{hgTV}$  error of a target variable due to a gross error equal to the threshold value
- *ehrmax* tolerance of error of a target variable due to random errors
- $e_{max}$  maximum value of  $e(1.96\sigma)$ , tolerance
- *F* flow
- *F* covariance matrix
- *g()* column vector of functions (A1-1)
- *h* target variable
- *p* pressure
- *q* dimensionless gross error (6-8)
- *t* temperature
- *Qmin* quadratic form of adjustments (A1-3)
- *v column* vector of adjustments  $\overrightarrow{A1-4}$ <br>*X* wetness of the steam (moisture conte
- wetness of the steam (moisture content in mass %)
- *x* column vector of measured variables
- *y* column vector of unmeasured variables
- *z* column vector of process variables
- $\alpha$  level of confidence, probability of the error of 1<sup>st</sup> kind (0.05 in this paper)
- $\beta$  probability that a gross error will be detected (0.95 in this paper
- $\nu$  degree of redundancy
- $\chi^2$ chi-square distribution
- *σ* standard deviation

# *Upper index*

- **'** reconciled value
- **<sup>+</sup>** measured value
- -1 inverse of a matrix
- *T* transposed matrix (vector)

## **Appendix 1: A very brief summary of Data Reconciliation**

Throughout this report it is supposed that the reader is a little bit familiar with mass and energy balancing and data reconciliation and validation. In special problems we will refer to our report [1] which is available free on the Internet. There are also books dealing with this subject [5-9].

Now only very briefly: Data Reconciliation (DR) can be defined as an adjustment of measured data to obey some mathematical model (mostly a law of nature). The DR procedure minimizes the generalized sum of squares of adjustments constrained by

$$
g(z') = 0 \qquad , \qquad (A1-1)
$$

where *z* is a vector of process variables (flowrates, temperatures, …) and *g(z')* is a vector of generally nonlinear functions of *z*. The vector *z* is partitioned

$$
z' = (y', x') \tag{A1-2}
$$

where *y'* is a subvector of unmeasured variables and *x'* that of measured variables.

The reconciled solution *z'* must obey the condition (A1-1) and minimizes the generalized sum of squares

$$
Q_{min} = \mathbf{v}^T \mathbf{F}^{-1} \mathbf{v} \tag{A1-3}
$$

where *F* is the covariance matrix of measurement errors and *v* the vector of adjustments of measured variables:

$$
v = x^3 - x^4 \tag{A1-4}
$$

where *x***'** are the reconciled values and *x +* the vector of measured values subject to random errors.

The solution is based on the assumption that true (unknown) values *x* are corrupted by random errors *e.*

$$
x^+ = x + e \tag{A1-5}
$$

Random errors are characterised by their standard deviations (sigmas). Sigma is calculated as the uncertainty of an instrument divided by 1.96.

The important notion is the *degree of redundancy*. If all unmeasured variables are observable,  $\nu$  equals the difference between the number of equations and the number of unmeasured variables.

This is a brief statement of the DR problem which is used in industry since early sixties of the past century. The solution proper was described many times in the literature and will not be treated here. Further it is supposed that the reader is acquainted with basics of DR. For those not familiar with the DR technology, there is the *Balancing and Data Reconciliation Minibook* [15] available free on the Internet. DR is also mentioned in [13].

Further it is also supposed that there exists a software which is capable of doing all necessary DR activities connected with DR – the DR Engine depicted in the next Figure A1.1.



**Fig. A1.1:** The Data Reconciliation Engine

We can write symbolically

$$
x' = h_1(x^+) \tag{A1-6}
$$
  

$$
y' = h_2(x^+) \tag{A1-7}
$$

where  $h_1(x^+)$  and  $h_2(x^+)$  are functions of measured values. By the "other information" in the Fig. A1.1 we mean other detailed results needed for data analysis described later (mostly covariance matrices of *x'* and *y'*).

The covariance matrices contain the all information about uncertainties of results. On their diagonals are squares of standard deviations (sigmas). The uncertainty is calculated as 1.96 times sigma. The uncertainties are in the RECON output reports denoted as "maximum errors".

# **Appendix 2: NPP data archive**

In the next Fig. A2.1 is the P&I diagram of the NSSS:



**Fig. A2.1:** P&I diagram. F – flow measurement, T – temperature measurement, P – pressure measurement

The directly measured variables shown in the Fig. A2-1 are accompanied by 3 other variables which are treated as measured with some uncertainty:



### *A2.1 Processing of one data set*

The summary of the one set of data (1 hour average) follows. Important are the uncertainties (column Max. error) given with sample values:

#### **Task: NRPOWER4SG (NPP with 4 steam generators) Input Data**

Balance: [10.07.2014 23:00; 10.07.2014 24:00)

#### **M A T E R I A L S T R E A M S**



#### **E N E R G Y S T R E A M S [MW]**



#### **T E M P E R A T U R E S [C]**





#### **P R E S S U R E S [MPAG]**



**W E T N E S S E S [%]**



### Results of this sample data reconciliation are shown next:

RECON 11.2.9-Pro [ChemPlant Technology s.r.o.] Task: NRPOWER4SG (NPP with 4 steam generators)

Balance: [10.07.2014 23:00; 10.07.2014 24:00)

#### **I T E R A T I O N S**



Legend:

Qeq mean residual of equations Qx mean increment of measured variables in iteration Qy mean increment of non-measured variables in iteration Qmin least-square function

#### **G L O B A L D A T A**





#### **E N E R G Y S T R E A M S**



#### **T E M P E R A T U R E S**



#### **P R E S S U R E S**



#### **W E T N E S S E S**



End of results

Calculations lasted 00:00:0.042

## *A2.2 Continuous data processing*

This Section is about processing of long term data by the program RECON. RECON can process data from more sources in one task (process historians, LIMS, relational databases, Excel files, …). In the following case data are stored in one sheet of an Excel file.

The process data are stored in the file HISTORY.XLS attached at this report. A part of this file is shown below:



The data format is as follows:

- 1. The first column contains the TIME information. For example, the time 1.7.2014 0:00 means the hourly average between 1.7.2014 0:00 and 1.7.2014 1:00
- 2. The first line contains tag names of variables
- 3. For the definition of this data structure are needed: Name of the time column (TIME in this case), the name of the Excel file (HISTORY.XLS in this case) and the name of the Excel sheet (G\_M in this case).

The data import is defined in several steps:

1. Definition of the data source on the following panel:



This panel defines the Excel file as a data source (EXC1), the sheet name and the time column name.

2. Configuration of the import is on the next panel:



Here the individual process variables are linked with the tag names in the HISTORY.XLS file.

After this configuration data can be processed with the aid of the following panel:



In general, data can be processed automatically for the selected time interval. In this case the input values are imported from the external data source (Excel file) and results are saved to the RECON's native database. It is also possible (in a different panel) to select just one data set for the interactive analysis of some special problems connected with data.

## *A2.3 Viewing and analyzing results*

Trends of measured and reconciled variables are available in the RECON's trend manager. Trends are configured on the following panel:

![](_page_63_Picture_42.jpeg)

Variables can be selected from the list or a user can create his groups of variables. Some examples follow:

![](_page_64_Figure_1.jpeg)

Trend of the FW1 flow. The blue line are the measured values, the red line are reconciled values. Peaks are caused by the periodic purge done usually once a day on the basis of the steam and condensate analyses. See the next figure:

![](_page_64_Figure_3.jpeg)

In the next figure is the trend of the NR power. The dot-dashed straight line represents the linear regression showing that the NR power decays a little bit in time.

![](_page_65_Figure_0.jpeg)

The next figure shows a trend of the Status of data quality (Status = Qmin/Qcrit, should be  $<$  1). The dashed line is the mean value. It can be seen that in the time interval selected no gross error was encountered. The average value of the Status is about 0.64. Some peaks in the Status trend correlates with periodic purges which evokes the increase of the relatively cold feed water into steam generators with the sequential disruption of the stationary state. Anyway, these relatively small disturbances do not influence the Status significantly.

![](_page_65_Figure_2.jpeg)

Let's now compare Status values with their theoretical mean value.

Qmin has the  $\chi^2$  distribution with v degrees of freedom. The mean value of this distribution equals  $v$ . In our case  $v = 9$  and the critical value (95 percentile) is 16.919. The mean value of the Status then should be  $9/16.919 = 0.53$ . We can see that the average Status value is not far from the expected vale.