DATA VALIDATION AND RECONCILIATION (DVR)

ON-LINE MONITORING, DIAGNOSTICS AND OPTIMIZATION + EXAMPLE

CONTENTS

GLOSSARY AND ABBREVIATIONS

a	adjustability of reconciled variables
DCH	Deaerated Condenser Header
DoR	Degree of Redundancy
DR	Data Reconciliation
DVR	Data Validation and Reconciliation
FWH	Feed Water Header
GE	Gross Error
GED	Gross Error Detection
MCM	Monte Carlo Method
NPP	Nuclear Power Plant
NR	Nuclear Reactor
NRTP	Nuclear Reactor Thermal Power
NSSS	Nuclear Steam Supply System
OLM	On-line Monitoring
Q_{min}	the Least Squares sum
S	Status of Data Quality
SG	Steam Generator
SH	Steam Header
TSM	Taylor Series Method
TV	Threshold Value
W	Covariance matrix of measurement errors
ν	Greek letter *Nu* – Synonym for Degree of Redundancy (DoR)
χ^2	Greek letter *Chi, random variable with* χ^2 distribution (see Eq. 2.19)
σ	Greek letter *Sigma*, standard deviation of a random variable
σ^2	variance of a random variable
σ_i	standard deviation of measurement error
$\sigma_{x'i}$	standard deviation of reconciled value
σ_{Vi}	standard deviation of adjustment

1 INTRODUCTION

Methods of process Data Validation and Reconciliation (DVR) are developed in process industries (chemicals, power generation and distribution) since sixties of the past century. Important is not only DVR proper but also related techniques like the optimal instrumentation placement, process data driven simulation and some others. There exist hundreds of papers about DVR which are compiled into several textbooks [2 – 9].

The development of DVR in power generation (in the steam cycle area and especially in NPPs) has evolved partially separately from the world - wide DVR stream. The main purpose of this Annex is to

- present shortly the basic theory behind DVR
- mention some new trends and methods which are still not commonly used in the NPP area
- present a short example illustrating the impact of DVR on on-line determination of NR thermal power.

2 MODELING INDUSTRIAL PROCESS SYSTEMS

The next Chapter 2 summarizes briefly theory of DR including some more advanced methods like measurement errors propagation and the Power of testing hypotheses about gross errors. There are many good books devoted fully or partially to these subjects [2-9]. The notation is taken over from the book [3].

2.1 Models

It is universally accepted that any measurement is charged with some error. The measurement error is defined by the following equation.

$$x^+ = x + e \tag{2-1}$$

where x^+ is the measured value
x is the true (unknown) value
e is the measurement error

Most frequently is supposed that e is a random variable with the Normal distribution with zero mean value characterized by the standard deviation σ. The standard deviation is supposed to be related with the *uncertainty* of the measured value. In technical practice is usually supposed that the uncertainty equals 1.96 times the standard deviation of the measurement error σ. This follows from the Normal distribution and the confidence level 95 %.

The frequently asked question is: Where to find values of σ or uncertainties? In [10,11] are defined two *types* of uncertainty: *Type A* uncertainty is estimated on the basis of measured data. *Type B* uncertainty is estimated by other methods (information from instrumentation vendors, published information, theoretical analysis of the measurement process, etc.) The *Type B* uncertainty is typical for application of DVR in the industrial practice.

Besides the model of measurement errors (2-1), DVR needs also the mathematical model of the industrial process itself. As was already stated earlier, the most common is the model based on First Laws of nature complemented by further thermodynamic calculations. Such model can have the form

$$\boldsymbol{F(x,y,c) = 0} \tag{2-2}$$

where ***F( )*** is the vector of implicit model equations (generally nonlinear)

- ***x*** is the vector of directly measured variables
- ***y*** is the vector of directly unmeasured variables
- ***c*** is the vector of precisely known constants

Typical measured variables ***x*** are process measured data like flowrates, temperatures, etc. Vector ***y*** contains usually unmeasured process variables but mainly also parameters of models (turbine efficiencies, etc.) and KPIs.

Note: Here should be noted that practically all statistical theory available holds strictly for linear models only [1]. The exit from this trap is the linearization of models by the Taylor Series Method. After the linearization, **results hold for the original nonlinear model only approximately**. The approximation depends on the model nonlinearity and also on the distance between true and measured values (measurement errors).

The important simplification of the nonlinear model (2-2) is so-called ***General Linear model*** (2-3) which can be obtained by linearization of the model (2-2) by the Taylor Series Method [10]:

$$\boldsymbol{A'x} + \boldsymbol{By} + \boldsymbol{a} = \boldsymbol{0} \qquad (2\text{-}3)$$

where

- ***x*** is vector of measured variables
- ***y*** vector of unmeasured variables
- **a** vector of constants

A' and ***B*** are matrices of constants

The General Linear model can be further simplified by elimination [3] of unmeasured variables to the form containing only measured variables (note that matrices ***A*** and ***A'*** are different):

$$\boldsymbol{Ax} + \boldsymbol{a} = \boldsymbol{0} \qquad (2\text{-}4)$$

2.2 Measured data reconciliation

Eq. (2-2) holds for the true (unknown) values of variables. If we replace them by the measured values $\boldsymbol{x^+}$, the equations need not (and most likely will not) be exactly satisfied:

$$\boldsymbol{F(x^+,y,c) \neq 0} \qquad (2\text{-}5)$$

whatever will be the values of the unmeasured variables.

The basic idea of DR is the adjustment of the measured values in the manner that the reconciled values are as close as possible to the true (unknown) ones. The reconciled values x_i' (marked by apostrophe) result from the relation

$$x_i' = x_i^+ + v_i \quad , \qquad (2\text{-}6)$$

where to the measured values, so-called *adjustments* v_i are added. In the ideal case, these adjustments should be equal to the minus errors, but these are unknown. If, however, we have the mathematical model that must be obeyed by the correct values then the optimal solution is as follows:

The adjustments must satisfy two fundamental conditions:

1) The reconciled values obey Eq. (2-2) – we say that they are consistent with the model

$$\boldsymbol{F(x',y',c) = 0} \qquad (2\text{-}7)$$

2) The adjustments are minimal. Minimized is the quadratic form

$$\text{minimize} \qquad \boldsymbol{v}^T \boldsymbol{W}^{-1} \boldsymbol{v} \qquad (2\text{-}8)$$

where $\boldsymbol{v}$ is the vector of adjustments v_i ($v_i = x_i' - x_i^+$) and $\boldsymbol{W}$ is the covariance matrix of measurement errors. In the case of uncorrelated (statistically independent) errors $\boldsymbol{W}$ is diagonal and the expression (2-8) has the form of weighted sum of squares

$$\text{minimize} \qquad \sum (v_i/\sigma_i)^2 = \sum [(x_i' - x_i^+)/\sigma_i]^2. \qquad (2\text{-}9)$$

where $v_i = x_i' - x_i^+$ are so called *adjustments*.

The inverse values of the standard deviations σ_i^2 – so-called *weights* – then guarantee that more (statistically) precise values are less corrected than the less precise ones (this is a relevant property of the method). This is the well known Method of Least Squares (or Generalized Least Squares in the case of expression (2-8)).

The reconciliation proper is the optimization problem requiring computer technique and effective software. In contrast to many other engineering calculations, the DR cannot be carried out manually (using a pocket calculator) even for very simple models.

The mathematics of the solution itself was in the last decades many times described in the literature (e.g. [2-9]) and will not be mentioned in the sequel.

So let us further suppose that at our disposal is some DR software ready to use for DR. Schematically, it is the Data Reconciliation Engine depicted in the following figure.

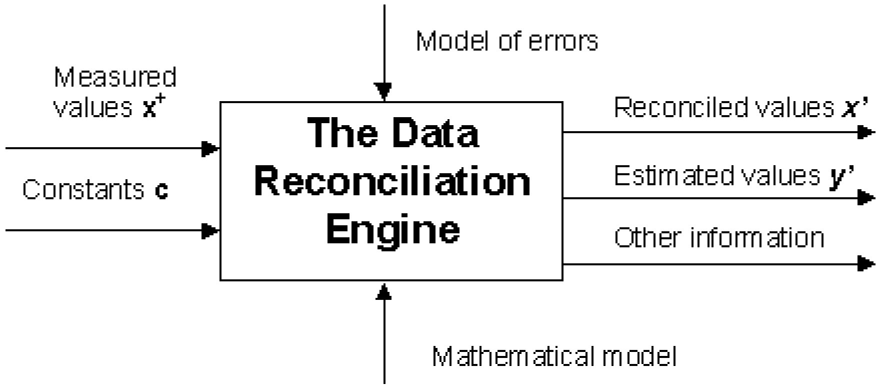

Fig. A2-1: The Data Reconciliation Engine

Note: The whole DR process (model linearization, elimination of unmeasured variables and DR proper applied to submodel (2-4)) requires efficient software. There exist two main ways how to find the minimum of (2-8). The first is so called Successive Linearization (SL) where the model (2-4) is used in the iterative way until the (2-7) model is zeroed (residuals of equations reach required minimum values). This relatively simple and fast algorithm has one drawback – the **zeroing the model (2-7) does not guarantee reaching the true minimum of the least squares sum (2-8) [15], p.137**. This fact is frequently overlooked. The second way is to use some of Nonlinear Programming (NLP) method, for example Successive Quadratic Programing, which not only zeroes (2-7) but reaches the real minimum of (2-8). Models of NPPs are not too much nonlinear and for a routine DVR calculations the SL method is sufficient. In special situations (e.g. GE identification) finding the exact minimum is important.

The reduced model (2-4) is used for DR proper. In the first step the adjustments ***v*** are calculated according to the equation

$$\boldsymbol{v = -\, WA^T(AWA^T)^{-1}(a + Ax^+)} \qquad (2\text{-}10)$$

Reconciled values ***x'*** are then calculated from the equation

$$\boldsymbol{x' = x^+ + v} \qquad (2\text{-}11)$$

by substitution from Eq. (2-10).

After reconciled values ***x'*** are calculated from Eq. (2-11), they can be substituted into Eq. (2-7) and unmeasured variables ***y'*** can be calculated. Symbolically it can be written as

$$\boldsymbol{y' = \mathbf{C}x^+ + \mathbf{c}} \qquad (2\text{-}12)$$

where **C** and **c** are matrix resp. vector of constants.

2.3 Statistical properties of results

Adjustments $\boldsymbol{v}$ have the normal distribution $N(\boldsymbol{0},\boldsymbol{W_v})$ and the covariance matrix of adjustments $\boldsymbol{W_v}$

$$\boldsymbol{W_v} = \boldsymbol{WA^T(AWA^T)^{-1}AW} \qquad (2\text{-}13)$$

The Quadratic form of adjustments (2-8) or (2-9) is the random variable with $\chi^2_{(1-\alpha)}(\nu)$ distribution with ν degrees of freedom. Values of $\chi^2_{(1-\alpha)}(\nu)$ for probability $(1-\alpha)$ are tabulated in statistical tables.

Between covariance matrices of measurement errors $\boldsymbol{W}$*, adjustments* $\boldsymbol{W_v}$ *and reconciled values* $\boldsymbol{W_{x'}}$ holds the **important** relation

$$\boldsymbol{W} = \boldsymbol{W_v} + \boldsymbol{W_{x'}} \qquad (2\text{-}14)$$

For variances of measurement errors, adjustments and reconciled values therefore hold

$$\sigma_i^2 = \sigma_{vi}^2 + \sigma_{x'i}^2 \qquad (2\text{-}15)$$

Square roots of variances (standard deviations) of reconciled values are important for estimating confidence intervals for results. On assumption of normal distribution of measurement errors it holds that with the probability 95 % the intervals

$$< x_{i'} - 1.96\ \sigma_{x'i}\ ;\ x_{i'} + 1.96\ \sigma_{x'i} > \qquad (2\text{-}16)$$

cover the (unknown) true values of individual variables.

Reconciled data are more precise in the statistical sense, if compared with the measured ones (this follows from Eq. (2-15)). The enhanced precision can be quantified with the aid of the standard deviation of the reconciled value, which is always smaller than the standard deviation of the measurement error.

$$\sigma_{x'} < \sigma \qquad (2\text{-}17)$$

The measure of the precision improvement is so-called *adjustability* defined as

$$a = 1 - \sigma_{x'} / \sigma \qquad (2\text{-}18)$$

The adjustability characterizes the reduction of the standard deviation and thus also the uncertainty of the result, if compared with the primary measurement. If for example the adjustability of the reconciled value is 0.5, the uncertainty has been reduced by half. The greater the adjustability is, the greater is also the reduction of the uncertainty.

2.4 Detection and elimination of gross errors

The term Gross Error (GE) means the measurement error which is highly improbable as being a random error, for example it is greater than three times the random error σ (the probability of such random error is less than 0.003). The cause of a GE can be random (single occurrence) but also systematic, caused for example by malfunction of some measuring instrument.

The process of DR is based on one model where all variables, measured and unmeasured, are tied together. This means that one measured value corrupted by some big error can influence resulting values of many other measured and unmeasured variables. This is well known effect of gross error(s) **smearing**. The protection of the DVR process against gross errors is therefore **essential**.

In the beginning it should be noted that many DVR users believe that it is possible to find all gross measurement errors present in the data set. As will be seen in the next, this is not possible. In general, possible gross errors belong to two groups:

1. Gross errors in redundant measured values which contradicts with other measured values. Such gross errors can be detected with some probability
2. Gross errors of measured variables which are not redundant and can't be detected during DR

There is also the issue of directly unmeasured but calculated variables (process variables, model parameters and KPIs. Results of these variables can be devalued by gross errors in measured values redundant and nonredundant. In what follows will be answered the following questions:

1. What is the probability to detect a gross error of some size (GE detectability)
2. How will GEs influence values of targets of the overall measurements (KPIs, Heat Rates, NR thermal power)
3. How to design a system protecting main results against GEs.

The most frequently used method for Gross Errors Detection (GED) is the test based on the value the least squares function (2-8) or (2-9). The Quadratic form of adjustments (2-8) or (2-9) is the random variable with $\chi^2_{(1-\alpha)}(\nu)$ distribution with ν degrees of freedom. Values of $\chi^2_{(1-\alpha)}(\nu)$ for probability (1-α) are tabulated in statistical tables.

If the value of the minimal value of the least squares function is denoted as Q_{min},

$$Q_{min} = \boldsymbol{v}^T \boldsymbol{W}^{-1} \boldsymbol{v} \quad , \qquad (2\text{-}19)$$

with *probability* (1-α) the value of Q_{min} will be less than the **critical value of the** χ^2 **distribution** with ν degrees of freedom.

$$Q_{min} < \chi^2_{(1-\alpha)}(\nu) \qquad (2\text{-}20)$$

Number of degrees of freedom ν is in DR solutions called **Degree of Redundancy (DoR).** In most cases for DoR holds that

DoR = *Number of model equations – Number of unmeasured variables*

Probability level (1-α) is usually supposed in technical sciences to be 0.95 (95 %) and this value will be used also throughout this text). All this holds on assumptions that only random errors with the Normal distribution are present.

Some software uses for GED slightly modified approach. The *Status of Data quality S* is defined as

$$S = Q_{min} / \chi^2_{(1-\alpha)}(\nu) \qquad (2\text{-}21)$$

Then the Eq. (2-20) reads

$$S < 1 \qquad (2\text{-}22)$$

If *S* is less than one, no gross error is detected.

The *S* definition has the advantage for an end DR user who does not need to know critical values for *Qmin* at different degrees of freedom. In words, a gross error is detected when the Status of Data Quality is equal or greater than 1.

It may be useful to note that the probability α is the **expected probability of the *Error of I*st *kind* (a Gross Error is detected even if it is not present).** In this report is supposed that α is 0.05. This means that we can expect 5 % of cases a gross error is detected even if it is not present.

Gross errors *detectability*

Gross errors *detectability* means that a gross error of some size will be detected with some probability. This problem is solved by so called *threshold values* which are characteristic for every measured redundant variable.

Let's recall the Eq. (2-1) defining a random error and let's modify it to the form

$$x^+ = x + e + d \quad , \qquad (2\text{-}23)$$

where d is a gross/systematic error (which is a constant).

One has to begin with testing the gross error presence hypothesis [3]. As any statistical test, also the χ^2 test has its power characteristic:

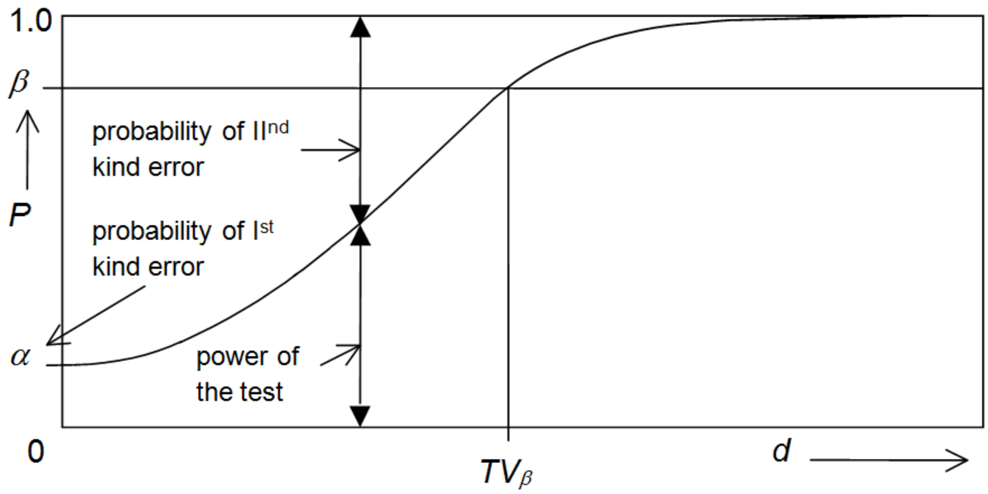

Fig. A2-2: The *power characteristic* of the χ^2 test

On the *x* - axis, we have the magnitude of the gross error *d*, on the *y* - axis the probability *P* of the gross error detection. The value given by the power characteristic for an adjustable measured variable equals the significance level α of the test assuming the absence of gross error (*d*=0), and it approaches 1 for high values of the gross error ($d \to \infty$). The value (1 – power of the test) is called *probability of* ***the IInd kind error*** (gross error is present but it is not detected).

The power characteristic represents though complete, but still too complicated information for the application in practice (imagine hundreds of such lines in a real size problem). Simpler is the characterization of measured variables by means of a single number, so-called *threshold value* (*TV*) for the gross error detection.

TV_β is the value of a gross error that will be detected with probability β (we'll further assume $\beta = 0.9$). TV_β is a characteristic value for any measured adjustable variable. The smaller TV_β , the better. TV_β is called the *threshold value*.

The threshold value can be computed from the equation

$$q_i = \delta_\beta(\nu,\alpha)/[a_i(2-a_i)]^{1/2} \qquad (2\text{-}24)$$

where q_i is dimensionless threshold value TV/σ

$$q_i = TV_i/\sigma_i \qquad (2\text{-}25)$$

and $\delta_\beta(\nu,\alpha)$ is a constant, characteristic for the significance level α of the *chi-square* test, degree of redundancy ν and probability of the gross error detection β. For more details see the literature [3], p. 177.

Values of $\delta_\beta(\nu,\alpha)$ for $\alpha = 0.05$, $\nu = 1,2,\ldots,500$ and $\beta = 0.90, 0.95$ and 0.99 are presented in [15].

Let us notice that for a measured variable, the threshold value is a simple function of its *adjustability* defined by Eq. (2-23); see also the following figure.

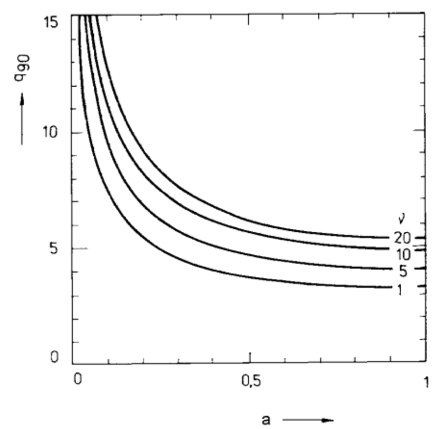

Fig. A2-3: Dimensionless threshold value *q* ($q = TV/\sigma$) as function of the degree of redundancy ν and adjustability *a* (for α=0.05 and β=0.9)

From this diagram, one can derive certain simple conclusions:

- The greater the adjustability is, the greater is also the probability that the gross error will be detected (low value of threshold error)
- For adjustability smaller than 0.05, the probability of gross error detection is very small and decreases further rapidly
- The minimum threshold value equals 3.24 times the standard deviation of the measurement (this in the case of ν = 1 and adjustability = 1, where *q* equals the minimum value 3.24). Considering that the maximum uncertainty is taken as 1.96 times the standard deviation, the minimum threshold value results as 1.65 times the uncertainty. From this finding follows that the method for gross error detection is not omnipotent even under optimal conditions and is effective only for gross errors significantly greater than supposed measurement uncertainty.
- Some DVR software does not acknowledge unmeasured process variables (flowrates, temperatures, etc.). Instead of it such variables are supposed to be “pseudomeasured” which means that some estimates with large uncertainties are entered as measured values. Such solution increase DoR significantly with the adverse effect on GE detectability (see Fig. A2.3).

3 STEPS BEYOND DVR

The benefits of DVR are quite clear:

1. Consistent data (data which are in agreement with laws of nature) are obtained
2. Reconciled data are more precise than the original measured data (have smaller uncertainty)
3. DVR provides information needed for detection, localization and elimination of possible Gross Measurement Errors, instrumentation malfunction, etc.
4. DVR provides information about uncertainty of reconciled values and also about uncertainty of directly unmeasured calculated variables and model parameters (heat transfer coefficients, turbine segments efficiencies, KPIs, etc.)
5. DVR provides information about propagation of measurement errors in the chain of further data processing. In this way it can help to optimize the whole measurement process. Typical tasks here are the analysis of replacement of existing instruments by more precise one, the optimization of instrument placement, etc.

To summarize, validated and reconciled data provide better information about the NPP performance.

The next question is: "How to recast this knowledge (gained after hard work and some money spent) into material benefits (improved heat rate, electricity production, higher profit, etc.)? Let's discuss some possibilities of better use of NPP data.

3.1 Process data driven simulation

DVR models can be classed among hybrid models. The core of the mathematical model contains equations based on the First Principles and thermodynamic calculations like phase equilibria, etc. This part of the model is usually created in the Graphical User Interface of some software. Such model can be complemented by user defined equations describing some special features of the plant. Important parts of the overall model can be empirical knowledge gained from equipment vendors or by the analysis of the long-term historical process data. As examples can serve characteristics of pumps, cooling towers, etc.

The frequency of DVR evaluation can be in the order of minutes. After the DVR step is completed, there are available values of model parameters (heat transfer coefficients, turbine segments efficiencies, etc.). Now, it is the time to use the model in the simulation mode. Model parameters are now inputs for calculations and outputs are values of process variables. In this way it is possible to answer so called What if? Queries, for example:

- What will happen if the ambient temperature will rise by 5 K?
- What will happen if the cooling water flowrate will increase by 10 %?

All this can be available for NPP operators as their decision support.

3.2 Parametric sensitivities

The existence of a model makes possible to calculate parametric sensitivities of calculated variables and important KPIs on model input variables. For exmple, how will be changed the heat rate if the heat transfer area of some heater will be increased by 10 %?

The table of parametric sensitivities should be available automatically after the DVR calculation is completed. Parametric sensitivities are useful for NPP optimization studies.

3.3 NPP Performance analysis and optimization

Factors that influence the overall plant economy belong to 3 categories:

- In the first category are External factors like ambient conditions, plant load. These factors can't be influenced by operators.
- In the second category are Internal factors which can be influenced by operators. This is the problem of the proper plant control.
- In the third category are losses caused by the Equipment degradation. This can be influenced by operators only partially, in some cases for example by cleaning of heat transfer areas. Some equipment degradation can require deeper maintenance.

A good Performance Analysis system should be able to separate the influence of three categories above and to quantify the amount of money which is lost by them.

The rest of this Section has no ambition to address advanced optimization methods like Real Time Optimization or optimization by a plant retrofit. For the off line optimization of a running plant we need to know:

The first: What is the real state of the system? This means complete and reliable mass and energy balance.

The second: To know the influence of control variables on the optimized KPIs. This can be solved by Data Driven Simulation or by Parametric Sensitivities

The third: How far are individual control variables from the optimum and what is their significance. This should be available for operators on the NPP Performance Dashboard.

4 EXAMPLE: DETERMINATION OF THE NR THERMAL POWER.

Steam generators (SG) in the 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 thermal power, the thermal power assessment is based on the detailed mass and energy balance of the SG system.

4.1 Nuclear Steam Supply System (NSSS)

NSSS for a PWR consists of the reactor and the reactor coolant pumps, steam generators and further equipment in the containment with associated piping. A detailed description of such system can be found for example in the IAEA document [13]. There exists also the ASME PTC [14] which is the Performance Test Code targeted at procedures for conducting tests to determine the thermal performance of a NSSS including assessment of the Nuclear Reactor Thermal Power (NRTP). 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

In words, the NRTP can be expressed as:

NRTP = SG power – Electric Energy inputs + Loss , (4-1)

The simplest is the case of the overall balance of the NR containment, which contains a NR and steam generator. The balance envelope is in the next Fig. A4.1:

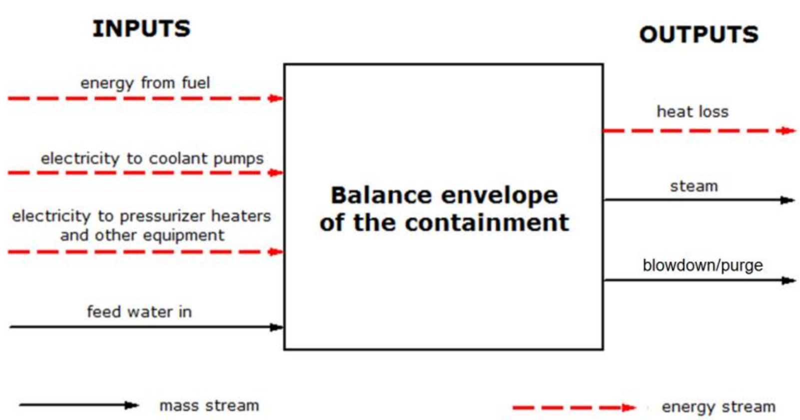

Fig. A4.1: Balance envelope of the containment

The NR thermal power (NRTP) 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 [14] 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 a steam generator.

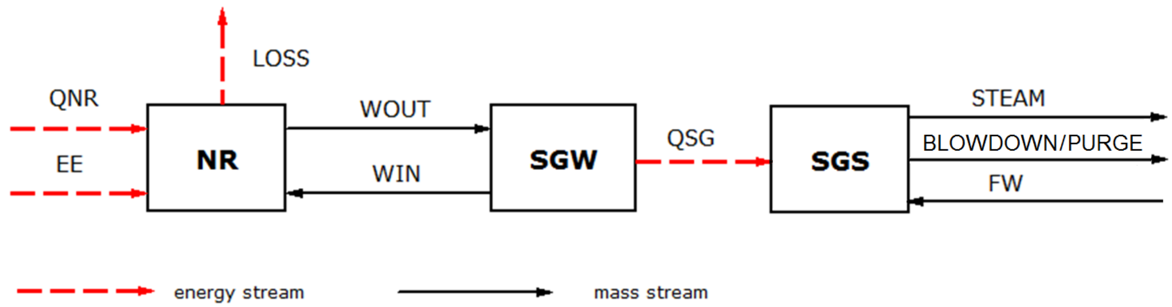

Fig. A4.2: Detailed balance flowsheet of the containment

The SGW means the hot water side of the SG, SGS means the steam side of the SG and QNR means the NRTP. QSG means heat transferred to the steam cycle. EE means electric energy input into containment.

In practice, there are usually 3 – 6 steam generators serving for one nuclear reactor. An example of the NSSS, the flowsheet of the VVER 1000 NSSS, is shown in the next figure:

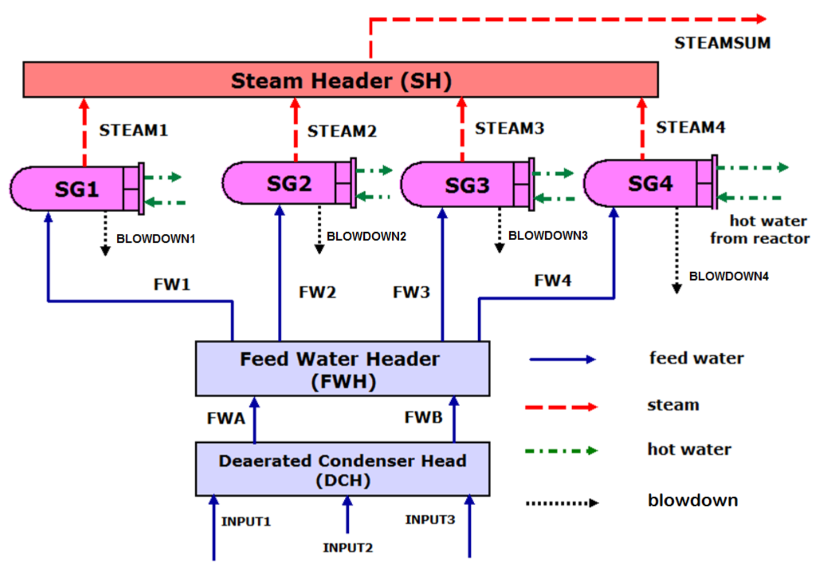

Fig. A4.3: The NSSS flowsheet

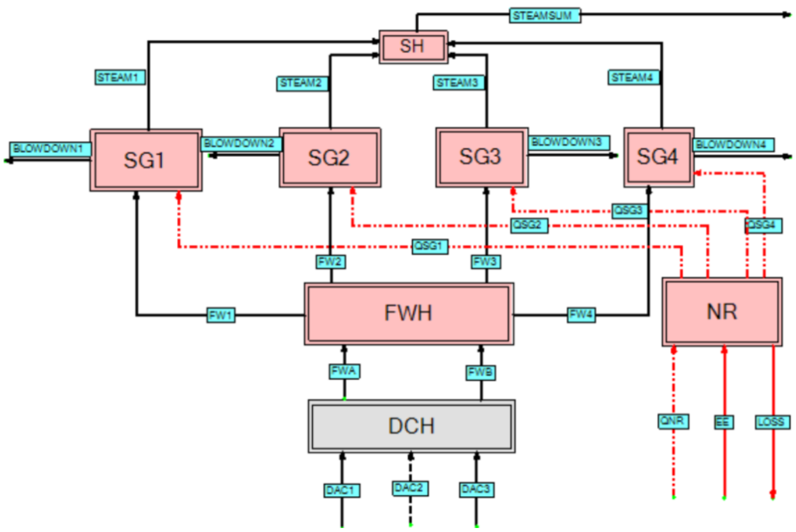

Fig. A4.4: Flowsheet for DVR [16]

Redundancy in such system stems from mass and enthalpy balances around 7 nodes and also from the temperature – pressure equilibria in steam generators (streams of steam). Let's suppose that there exist flowmeters on all streams of deaerated condensate (DAC), feed water at two levels (FW), steam from SGs and blowdown streams. Further, pressure and temperature are measured on all streams. In this example the following measurement uncertainties were supposed:

Table A4.1: Measurement uncertainties

Type	**Stream**	**Uncertainty**
Temperature	All	1 ºC
Flow	STEAM	1.8 %
Flow	BLOWDOWN	3 %
Flow	FW	1.2 %
Pressure	All	0.5 %
Electricity input	EE	1%
Heat loss	LOSS	20 %
Wetness	STEAM	0.05 %

4.2 Influence of redundancy on the NRTP uncertainty

As can be seen from Fig. A4.3, there are several redundant measurements on the feed water streams between the deaerated condensate header and individual steam generators. This redundancy can be used for improving the reactor heat power accuracy (lowering its uncertainty). There exist also other benefits stemming from data reconciliation which will be studied later.

In the next table are uncertainties U of NRTP calculated for several variants of data redundancy (DoR), starting from the nonredundant system described in [14] to the system with maximal redundancy.

Table A4.2: Uncertainties U of NRTP for different variants of redundancy

No	Variant	DoR	U [%]
1	Balanced SGs, steam flows unmeasured	0	0.623
2	Variant 1 + measured SG steam flows + balance around SH	6	0.504
3	Variant 2 + balance around FWH	8	0.438
4	Variant 3 + balance around DCH	9	0.396
5	Variant 4 + water-steam equilibrium in SGs	14	0.396

It can be seen that the influence of redundancy on NRTP uncertainty is not negligible. Variant 1 recommended in [14] with zero redundancy has uncertainty 0.623 % while Variant 4 with DoR = 9 has uncertainty 0.396 %. The difference 0.227 % represents 2.27 MWe in the case of 1000 MWe nuclear block.

4.3 Parametric sensitivities and propagation of measurement errors

According to (2-12), calculated unmeasured variables are approximately linear functions of measured variables. It is therefore possible to estimate their sensitivities to measurement errors. Parametric sensitivities (PS) of NRTP to values of selected measured variables for Variant 4 are presented in the next table:

Table A4.3: REPORT ON PARAMETRIC SENSITIVITY

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Variable Heat Flow  NRTP         NR heat power

 GIVEN VARIABLE IS SENSITIVE TO:
Type Measured variable    Sensitivity  Unit
 ------------------------------------------
  HF  EE                       -1,000  [MJ/S] / [MJ/S]    electric energy input
  HF  LOSS                      1,000  [MJ/S] / [MJ/S]    heat loss
  MF  BLOWDOWN1                -1,262  [MJ/S] / [KG/S]    blowdown from SG 1
  MF  DAC1                      0,359  [MJ/S] / [KG/S]    deaerated condensate 1
  MF  FW1                       0,721  [MJ/S] / [KG/S]    feed water 1
  MF  FWA                       0,366  [MJ/S] / [KG/S]    feed water A
  MF  STEAM1                    0,321  [MJ/S] / [KG/S]    steam from SG 1
  MF  STEAMSUM                  0,079  [MJ/S] / [KG/S]    steam to the tubine
  T   FWA                      -1,193  [MJ/S] / [C]       feed water A
  T   FWSG1                    -1,131  [MJ/S] / [C]       feed water to SG1
  T   SG1                      -0,141  [MJ/S] / [C]       steam generator 1
  T   steamsum                 -0,140  [MJ/S] / [C]       sream header
```

```
 X   SGsteam                  -25,541  [MJ/S] / [%]       wet steam

Legend:

 HF  Heat flow
 MF  Mass flow
 T   Temperature
 X   Steam wetness
```

For example, the PS = 0.721 means that the increase of FW1 measured flow (for example caused by a measurement error) by 1 kg/s will cause the change of calculated NRTP by 0.721 MW.

Equation (2-12) is also basis for calculating propagation of measurement errors during calculation of final results. The variance (σ^2) of a resulting value is the sum of contributions of individual measured variables (so called shares of measured variables). The information of shares for NRTP is shown in the next table:

Table A4.4: THE VECTOR OF SHARES

REPORT ABOUT PROPAGATION OF ERRORS

==================================

Heat flow NRTP NR Thermal Power

THE VARIANCE OF GIVEN VARIABLE IS CAUSED MAINLY BY:

Type	Measured variable	Share	
MF	DAC1	9 %	deaerated condensate 1
MF	DAC3	9 %	deaerated condensate 3
MF	FW1	8 %	feed water 1
MF	FW2	9 %	feed water 2
MF	FW3	9 %	feed water 3
MF	FW4	9 %	feed water 4
MF	FWA	9 %	feed water A
MF	FWB	9 %	feed water B
MF	STEAM1	4 %	steam from SG 1
MF	STEAM2	4 %	steam from SG 2
MF	STEAM3	4 %	steam from SG 3
MF	STEAM4	4 %	steam from SG 4
MF	STEAMSUM	4 %	steam to the turbine
Sum		92 %	

There are 32 measured variables in the NSSS model. 92 % of the NRTP variance is caused by 13 measured variables in Table A4.4. The total contribution of remaining 19 measured variables is 8 % only. It is clear, that for lowering the overall variance (NRTP uncertainty) is important to cut down uncertainty of flowmeters in Table A4.4, especially flowmeters of feed water (better maintenance, calibration, installation of more precise ones). The opportunities of other measured variables are from this point of view negligible.

4.4 Gross errors detectability

In Section 2.4 was solved the following problem: What is the probability that a gross measurement error will be detected at all? Every redundant measured variable has its own Threshold Value (TV). A gross error greater than TV_β will be detected with probability greater than β. It was shown that TV_β depends on the adjustability of the variable, uncertainty of the measurement proper and also on Degree of Redundancy of the model. In the next table are some selected redundant variables with their TVs.

Table A4.5: REPORT ON GE DETACTABILITY

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 Beta: 90%	Beta: 95%	Beta: 99%	Unit
MF	BLOWDOWN1	0,000099	17,325	18,897	21,798	KG/S
MF	DAC1	0,217824	33,303	36,324	41,901	KG/S
MF	FW1	0,210281	16,385	17,871	20,615	KG/S
MF	FWA	0,228623	33,099	36,102	41,646	KG/S
MF	STEAM1	0,473045	17,728	19,336	22,305	KG/S
MF	STEAMSUM	0,793117	65,213	71,129	82,051	KG/S
T	FWA	0,184960	3,923	4,279	4,936	C
T	FWSG1	0,038540	8,268	9,018	10,402	C
T	SG1	0,024335	10,367	11,307	13,044	C
T	steamsum	0,552660	2,542	2,772	3,198	C

Legend:
Adjustability = relative cut of error due to reconciliation
Threshold value = gross error that will be detected with probability Beta

MF Mass flow
T Temperature

For example, for beta = 90 % the flowrate FWA has TV_β = 33.099 kg/s. The flowrate of FWA equals 368.5 kg/s. TV is therefore ca 9.0 % of the measured value.

The flowrate STEAM1 has TV_β = 17.728 kg/s. The flowrate of STEAM1 equals 368.2 kg/s. TV is therefore ca 4.8 % of measured value.

The knowledge of GE detectability plays role in protection of target results (e.g. NRTP) against gross errors. Two factors should be taken into account:

1. TV of the redundant variable (the lower TV the better)
2. Parametric sensitivity of the measured variable to the target result (the smaller the better).

It is not possible to present this a little bit complex technique in this Annex. The complete solution of this important problem can be found in [15].

5 DISCUSSION AND CONCLUSIONS

DVR is nowadays the matured method of analysis of operating NPPs. There are two areas of its use: (a) Performance tests of new or reconstructed NPPs and (b) Daily monitoring and on/line analysis (OLM) of running NPPs. These areas differ significantly. Performance tests can use special portable instruments and it is supposed that all measuring instruments are functioning properly. The OLM can rely on standard instrumentation only. If some measuring instrument is out of order, it must be eliminated from the input data set until it is repaired. In the meantime, it can be replaced by calculation from other variables (if it is redundant).

The methods presented so far were based on more than 60 years of DVR development in the world wide DVR community. One example of DVR application in NPPs can be the TEMPO software developed in the framework of the OECD Halden Reactor Project [17]. We have not commented here the DVR stream of the German Standard [12] which was originally written for acceptance tests. The basic recommendations following from this Annex are:

1. The basis of the NPP model can be the combination of First Laws (balancing), thermodynamic calculations and empirical relations based on data from equipment vendors and historical NPP data (the hybrid model)
2. The minimization of the Least Squares function [2-8] should be done by some nonlinear programming method to guarantee finding the true minimum.
3. All available methods for Detection, Identification and Elimination of Gross Measurement Errors should be applied.
4. All information contained in results should be extracted: uncertainties of results, parametric sensitivities, info about propagation of measurement errors, threshold values, etc.
5. The DVR model can be the basis for Process data driven simulation, What if? Queries, etc.

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