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Power Plant Performance Monitoring Using Statistical Methodology Approach

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Abstract

The paper sets out problems experienced in current power plant performance calculation methodology. With changes in the electricity market and the increased role of computer control and diagnostic system, the previous methodology is fast becoming obsolete. Several key factors are highlighted (for example, reference values and corrective curves) which may lead to highly imprecise and inadequate evaluations of plant performance and, especially, operator behavior. It is important to bear in mind the systemic changes on the energy market. The current methodology focuses on controlling factors impacting power generating efficiency whereas the modern market is more complex and real costs are largely dependent on other variable costs, such as environmental fees, equipment wearing costs and the energy trading market .

Statistical analysis of data is proposed as a modification of the current methodology. As most heat rate calculation is done on-line, it is possible to analyze this data in detail and apply, for example, PCA (Principle Component Analysis) and linear (and nonlinear) regression, thereby enabling a more accurate determination of the influence of principle process parameters on heat rate deviation. The article presents sample results of comprehensive analysis (two cases from different plants) of two twin units (heat rate calculation and process data analysis from a 12-month period) which to demonstrate the clear need to modify and update the old performance calculation approach.

1. Introduction

The method of performance monitoring used at present was developed over 30 years ago for units operating in the conditions expected for the power sector of the time. That methodology corresponded to the American and Western Europe standards of the 60s and 70s, which put reliability first. This method delivered significant advantages in the form of higher quality performance monitoring, but today seems outdated in the context of the current dynamic deregulation of the power generation industry.

This older approach is becoming less viable as a true performance index of plant capability due to the two basic factors – advanced computer technology enabling widespread use of digital automatic control systems and system changes in the energy market.

Digital computer based automatic control systems have made it possible to provide almost non-stop performance control through direct operator supervision and the monitoring of all performance parameters (and losses) on-line. The increase in the quality of measurement devices and tools has reduced the role

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of periodic heat rate testing and warranty measurements. The high quality of the DCS automatic control connected with the more common application of optimization systems (really substituting operator actions during normal unit operation) has reduced the possibility of a simple improvement of efficiency indexes. For this reason, the principle role of performance supervision should be modified for the need to detect possible losses from unit operation [unsure] in market based generation dispatch.

This article proposes using statistical data analysis to improve aspects of the current performance monitoring systems. Due to the special characteristics of European power plants, we use as reference a large coal fired generation asset both in the presentation of theoretical material and in practical results.

It is important to bear in mind the system changes that have taken place in the energy market. The current methodology focuses on controlling factors connected with the efficiency of the energy production process (and thus only takes into account the cost of fuel). The market nowadays is more complex and the real costs (and losses) are largely dependent on other variable costs, such as environmental credits/costs (emissions and the future influence of emissions trading), maintenance factors (maintenance and repair costs, and costs connected with the operation of a deregulated energy trade market (e.g. filling in contracts, possibility of spot transactions, etc.). What is postulated is modifying the method in the direction of Market Performance Control, as it affects all the above issues. That, however, lies outside the scope of this article.

2. Current Performance Monitoring

The typical performance monitoring methodology is presented in numerous conference materials. In short, it is based on calculating the unit chemical energy usage rate (ASME Power Test Codes) and assigning the measured losses deviations of the unit chemical energy usage rate from the expected value (nominal, or resulting from the last design or warranty measurements), following from operating the unit at parameters other than the nominal parameters [1, 2]. The basic parameters whose influence over the unit heat rate is usually taken into consideration are as follows: main steam pressure, main steam temperatures, pressure drop in the superheater, reheat steam temperature, condenser pressure, feedwater temperature, oxygen content in flue gas, flue gas temperature.

Whereas the number of controlled parameters has been expanded many times, the theoretical basis of this method remains the same. The deviation [kJ/kWh](BTU/kW) was usually calculated to a value of dollars/kWhour for a more visual presentation of data. Systems based on ASME or similar methodology were introduced in practically all power plants, with the modernized automatic control systems usually developed into on-line systems performing all the calculations every few minutes and presenting the results on operators' screens at the DCS or auxiliary computer displays.

3. Performance monitoring – the problems of conventional application

The performance calculation methodology, though no doubt necessary and effective when properly implemented, also has a series of drawbacks. It is apparent that after so many years (and many platform revisions to calculate results) it is possible to evaluate the results more critically and to attempt a more in-depth analysis.

The basic problems with the current performance monitoring application:

- **Reference values** – most deviations and losses are calculated and monitored against reference values – usually the nominal values given by the OEM manufacturer. For devices often with a 10–20 year life cycle and upgraded on numerous occasions these nominal values do not constitute a real reflection of the actual as found parameters.

- **Correction curves for defining the controllable losses (measured losses)** – the influence of operational parameter deviation (temperature, pressure etc.) from the assumed values (achievable, design, theoretical...) is assigned largely using the so-called manufacturer's correction curves. Leaving aside the accuracy of these curves and the problems commonly encountered in obtaining this data, the basis of

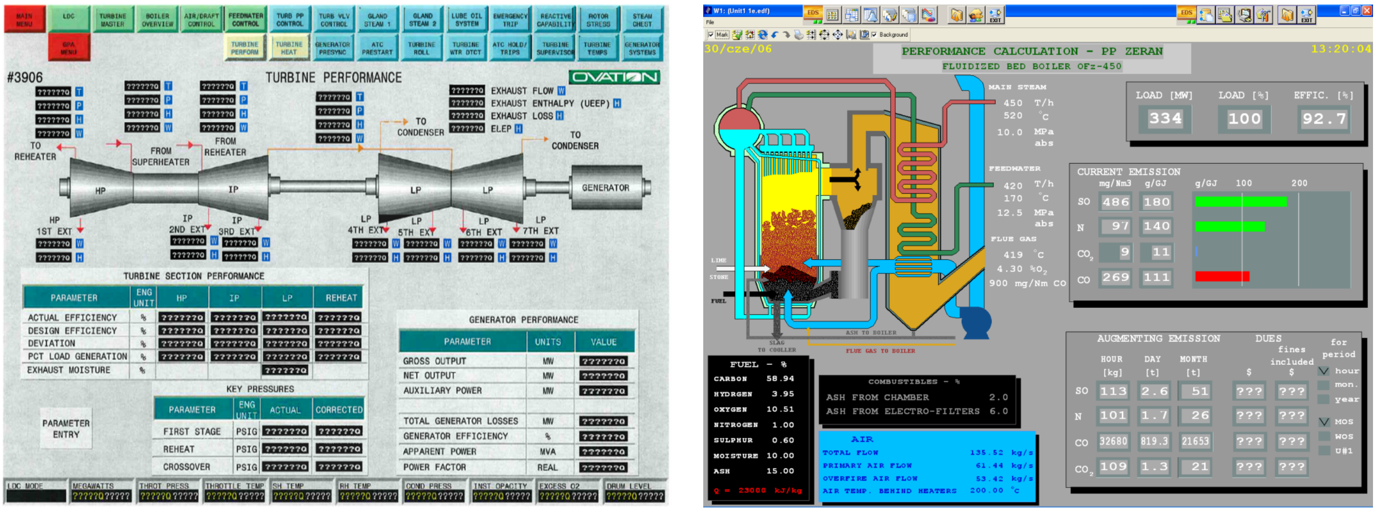


Figure 1: Examples of typical operator's graphics showing the results of on-line performance monitoring calculations for process operators – Europe (left), US (right)

this theory is to define the influence of these parameters (x_i)(gradient) as a unit heat rate (q_b) – $\partial q_b/\partial x_i$ but the manufacturer's data does not necessarily correspond to the real, dynamic operation of a maintained unit. On the other hand there seems to be a serious theoretical problem with assigning the deviation for the given control value. In the case of building a correction curve, it is assumed that a clear assignment of the influence of a given value on the unit heat rate will be possible (q_b). In other words, variables such as pressure, temperature, etc are treated as independent variables (this results, among others, from the method of assigning correction curves through balance calculations and the change of an individual parameter in simulation calculations) which finally leads to obtaining a dependence $\partial q_b/\partial x_i = f(x_i)$. In actual practice, a strong relationship exists between these parameters (they are interrelated – e.g. in the form of a turbine equation) – in brief, during normal operation it is not possible to change one parameter without modifying a number of others. Additionally, assigning relationships between these parameters is not only dependent on the thermodynamic dependencies (balance) but is also influenced by the operation of the automatic control system controlling the unit. In other words – in practice when changing one of the main unit operational parameters, the automatic control systems perform a shift of the unit status into a different operating point (also modifying the other parameters). Because of this, deviations assigned using correction curves cease to have any practical significance. For example, even if at a given moment we assign deviations of a unit heat rate for a series of main parameters (and we obtain a negative deviation for one of them, resulting from the difference between the current and the nominal value – referential), then in the case of canceling this difference (bringing the parameter to the nominal-reference value – and thus reducing the deviations), all the other parameters will remain unchanged (!), and we will obtain a entirely different system of parameters, and their differences from reference values, and as a result completely different values of non-measured deviations.

- **Separating startup from normal performance** – the procedures of calculating startup losses are commonly used (and are typical) – but they allow assignment of higher and predicted losses during startup – and not a "smooth" shift to losses during normal operation modes.

- **Applying statistical balance models for assigning losses during load following unit operation** – models used in performance monitoring are based on a strictly static approach and in order to obtain good results they require a good thermal status (or quasi-static) isolation of the unit operation – in the simplest approach this requires a momentary stabilization of unit power and its principle parameters. In the conditions of the present (ISO or deregulated market) situation this is simply impossible – in fact the entire regime of condensation unit operation actively participating in the power market is based on operation during dynamic (ramping or transitional) states. Using this methodology for temporary (dynamic) performance monitoring might seem questionable in light of the typical approach for obtaining good global results (characteristics, optimization), where it is common to use diverse static processing of performance data, which averages the results (considering the normal distribution of calculation errors and influence of dynamic states) and cancels momentary errors.

4. Postulated change

This postulation focuses principally on two basic problems: of reference values and the possibility of evaluating performance deviations on the basis of reference curves. Putting theoretical considerations into practical questions, these two problems boil down to the following questions (and attempts to derive answers!):

- **What are the currently achievable unit parameters?** Units constructed in the 70s and 80s have been subject to various upgrades and maintenance repairs. A large part of the utility generation assets burn fuel which significantly differs from the original design values. The basic equipment (boiler, turbine) has been repaired/rebuilt and modernized. In practice this often means that we are faced with a completely different site than the one originally envisioned by the design team and performance monitoring analysis involves large deviations (both positive and losses) which the process operator is unable to eliminate. These deviations result from a long-term change in unit operation parameters. Assigning deviations in this case for given projects seems impractical and devoid of purpose. It may however be meaningful to evaluate losses (or the possibility of performance improvement) in relation to average values (achieved throughout long-term performance) or the best practices observed during performance.

- **Which performance losses are the most significant ones and which can actually be improved?** In industrial practice the real evaluation of deviation is important (heat rate) (cost of deviation); using a correction curve to assigning this value seems far from perfect. In the past the advantages of the present method were advertised as, for example, the possibility of calculating how much it costs to operate a unit with parameters different than the nominal ones. Even if by nominal parameters we mean optimal parameters (the best achievable), then by making direct use of the current method and correction curves we will obtain an idealized (and thus fictional and practically nonexistent) solution. Theoretical assumptions of this method assume that the influence of each of the parameters can be treated individually and that it is possible to change each one of them to the reference value without changing the other parameters. This is not possible in normal unit performance. It seems purposeful to search for a method which would at the same time identify the losses (deviations) that can be reduced and the real influence of process parameters on the effectives of unit operation (taking into consideration real unit characteristics and thus, the reaction of automatic control systems).

4.1. Extending the possibility of performance monitoring through a deep statistical analysis of process data

When equipping the power units with a digital automatic control system, the heat rate calculations are in practice conducted on-line, so we have a large volume of calculation data whose statistical analysis may turn out to be a valuable tool for correct reasoning. Of course, we assume that in the case of performance analysis conducted on-line we are aware of measurement-calculation problems (and ways of solving them) such as: credibility of measurement devices (it is assumed that the basic measurement tools (especially flow measurements) operate correctly and are of an appropriate measurement class, the influence of delayed chemical analysis of fuel (when there are no on-line analyzers), process data and results are appropriately processed to eliminate measurement errors and filtering the non-stationary statuses of units, etc. After solving these problems, we finally possess a large, credible base of calculation data and unit heat rate for various unit operating states. Some similarity to the proposed approach may be found in [3–5].

4.1.1. Statistical analysis

The primary objective of this analysis was to create histograms and assign mean values of process parameters and comparing them with process values. This will allow one to check how real the performance parameters are (mean values and the most common ones) against reference values (nominal). Thanks to current automatic control systems it is now possible to archive data from a practically unlimited period of performance, and create an unlimited database. When assigning the basic reference operating parameters it is postulated to aggregate the data in unit efficiency data (steam flow, power). The calculation examples present only the results for an arbitrarily accepted power range 120–160 MW (low power) and 160–200 MW (high power) (corresponding to the typical performance regimes). In the developed form of course, it is possible to obtain a function of any parameter depending on the efficiency (power) of a unit.

4.1.2. PCA

PCA – (Principal Component Analysis) is a method which makes use of linear transformation to, change input variables into new variables (‘principle components’) which are uncorrelated. PCA is an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA can be used for dimensionality reduction in a data set while retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data.

This transformation retains all the most important information concerning the original variables. In particular, the first component shows the direction of the biggest dispersal of analyzed variables. Referring to this specific analysis of performance data through PCA, it is possible to:

- Assign new variables (fictional) – each is a combination of the basic and process parameters, not correlated.
- Assigning the first component of PCA – and through its analysis to identify parameters with the highest changeability.

4.1.3. Analysis using the linear regression model

The principle objective of the analysis is to build an empirical (linear at this point) model of unit heat rate in the form of a function $f : R^d \to R$ linearly dependent on main technological parameters and defined by the formula $f(x) = < x, w > -\gamma$, directly applicable to unit heat rate approximation in the form as

$$q_b = \sum_{m-j}^{m} a_j x_{1,j} + ... \sum_{m-j}^{m} a_{n,j} x_{n,j}.$$

A model of this kind can make it possible to assign the direct influence of a given parameter over changeability qb (and more precisely, on its empirical model). With such an approach we may obtain a similar (linear) function to that obtaining in most corrective curves.

A linear regression model constitutes the simplest empirical approximations of unit heat rate from the basic process parameters. It is possible to construct such a model with sufficient accuracy, the next step is to assign the correlation of basic parameters which directly leads to assigning the influence of these parameters onto the unit heat rate. Of course, the linear regression model can then be modified (nonlinear models, neural networks, fuzzy networks, etc.) to improve mapping accuracy.

5. Calculation examples

The conducted tests use calculation data of the unit heat rate of two of the Polish power plants. In each case, analyses were conducted for two similar units – 225 MW of identical construction with twin automatic control systems. The results (appropriately averaged and aggregated in appropriate ranges of unit power) of the current performance calculation covering an approximately 12-month period were used for the purposes of analyzing the data. To simplify the analysis results, the article lists three histogram values for two load ranges – low (120–160 MW) and high (160–200 MW). The table below presents data analysis results for both unit – histograms and principle statistical measures for appropriate power ranges.

The statistical analysis leads to a series of conclusions:

- Even the most similar power units have different performance characteristics and different histograms of the basic parameters.

- In many cases the current process values (obtained during operation) are significantly different than the nominal values (often assumed as referential) and can vary significantly depending on the unit power range (boiler efficiency) – for example, the reheat steam temperature for unit *A* at low loads has an average value of 526 °C and very high changeability (standard deviation) – case a in the figure in Table 2.

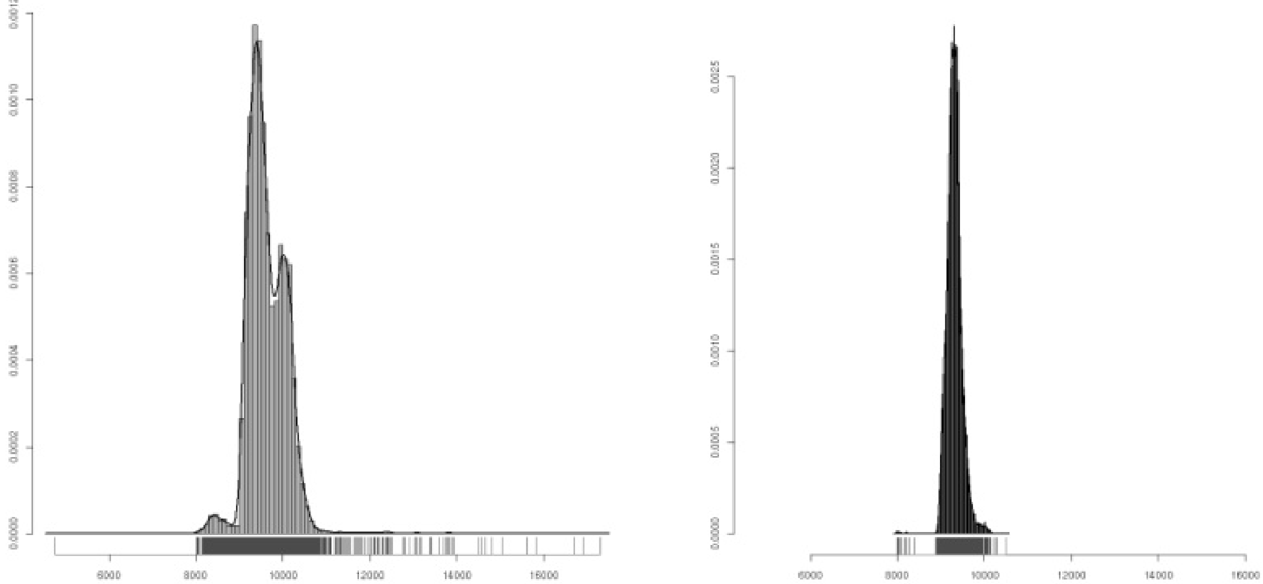
- Observing the changeability of a certain parameter (standard deviation) allows one to draw conclusions on the level of tuning of the automatic control system – unit *A* during low load operation has a significant problem with achieving the design level of reheat steam temperature (case a in the figure in Table 2).

- Observing O_2 concentration in the boiler (figures in Table 3) below, we may compare the performance of units *A* and *B* (and therefore the influence on boiler efficiency and unit heat rate). In boiler *A* we find a characteristic twin peaks histogram (case b Table 3) – with these boilers optimization systems are implemented and higher O_2 values are achieved when the system is off. In boiler *B*, the optimization system was practically in continuous operation, resulting in better O_2 control.

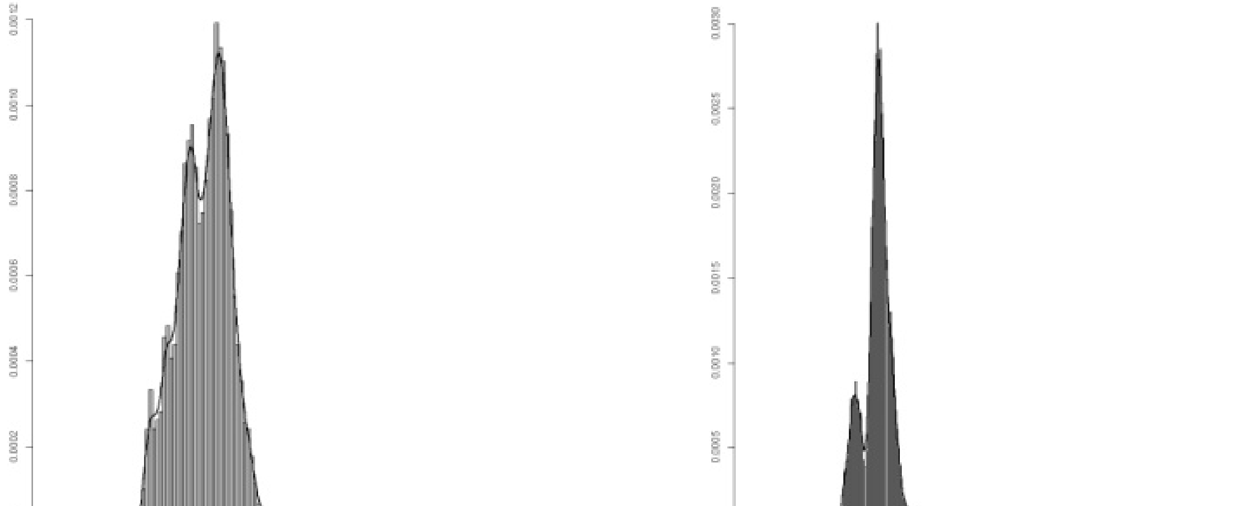
PCA analysis seeks to identify process parameters with the highest changeability by transforming them into a set of independent (uncorrelated) parameters. See below for the first principle component of the two units. The participation of a given process parameter in the principle component is presented by the bars on the chart – the number of the variable on the x axis corresponds to main steam pressure (1), main steam temperature (2), reheat steam temperature (3), pressure drop in the superheater (4), feedwater temperature (5), condenser pressure (6)).

PCA enables swift identification of parameters leading to the biggest changes in unit heat rate. In this specific example, the calculation for unit *A*, it is the temperature of reheat steam for low loads (variable no. 3). For unit *B*, the parameters which have the highest changeability are pressure drop in the superheater and pressure in the condenser (changeability caused by seasonality), thus one can assume that there are no significant performance problems for this unit. In the next step, an approximation of heat rate (q_b) was performed using linear regression. This analysis method is simply an empirical (based on historical data) model approximation (prediction) of the unit heat rate. Although the results obtained indicate the possibility of only a very rough estimation of q_b, model correlation is much higher than the correlation of a single variable. The correlations of basic parameters allow one to evaluate the influence of a given parameter on q_b.

The results confirm the previous conclusions from the statistical analysis. As long as the correlations of process variables for high powers are at a high level (none of the process parameters are responsible for substantial changes in q_b), at a low level of power we can see the visible dominant influence of reheat steam temperature (variable no.3), which largely reduces unit performance. One may be tempted to test the qualitative influence of this parameter. Linear regression leads directly to obtaining the dependence (linear) of influence of a given parameter to a change of correlation of unit heat rate. This values was then compared against the data from the correction curve

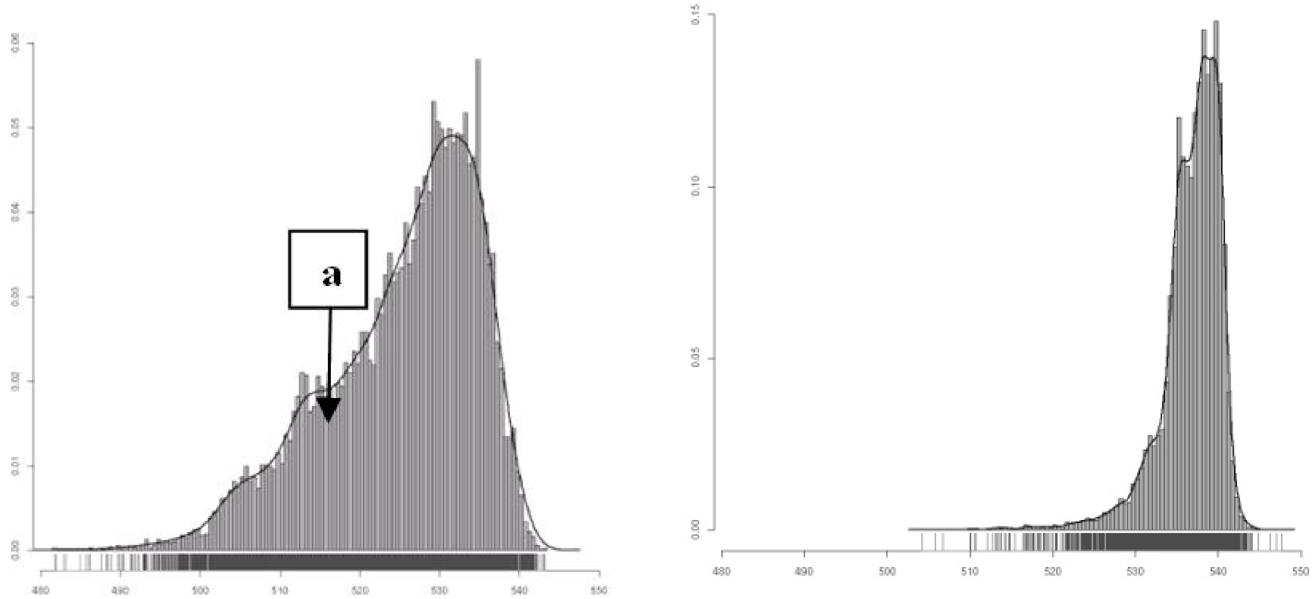


Unit A unit heat rate [kJ/kWh] average I (low load) left – 8850 II (high load) right – 8630
Median I – 8840 II –8638 Std, Dev. I –397 II –174

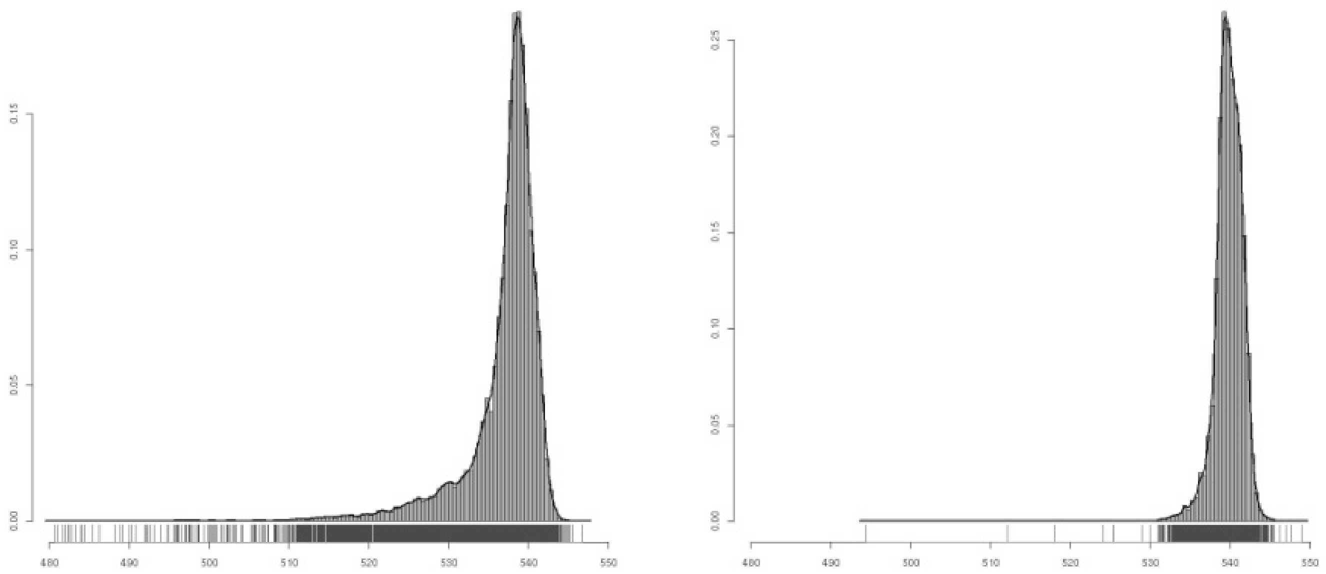


Unit B unit heat rate [kJ/kWh] average I –8756 II – 8107
Median I – 8787 II – 8425 Std, Dev. I – 353 II – 214

Table 1: Results of statistical analysis of the principle performance parameters – heat rate; analysis from plan #1

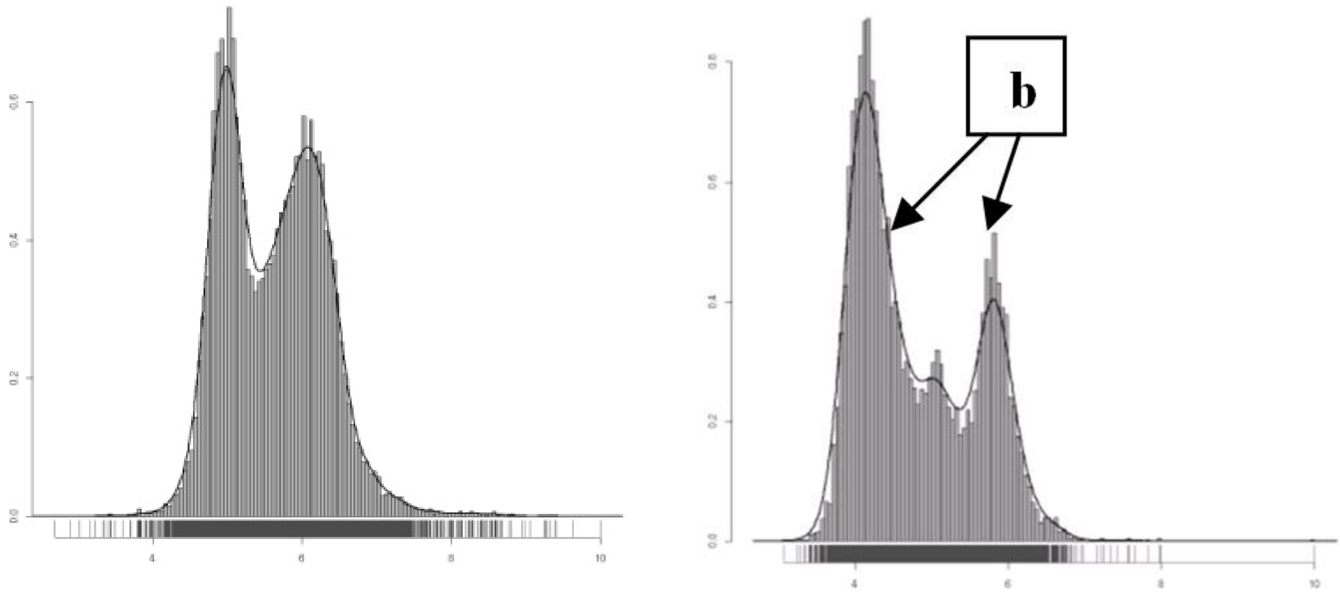


Unit A t_{wt} [°C] reheat steam temperature average I –525.2 II – 536.45
Median I – 536.7 II –538 Std, Dev. I – 9.55 II –4

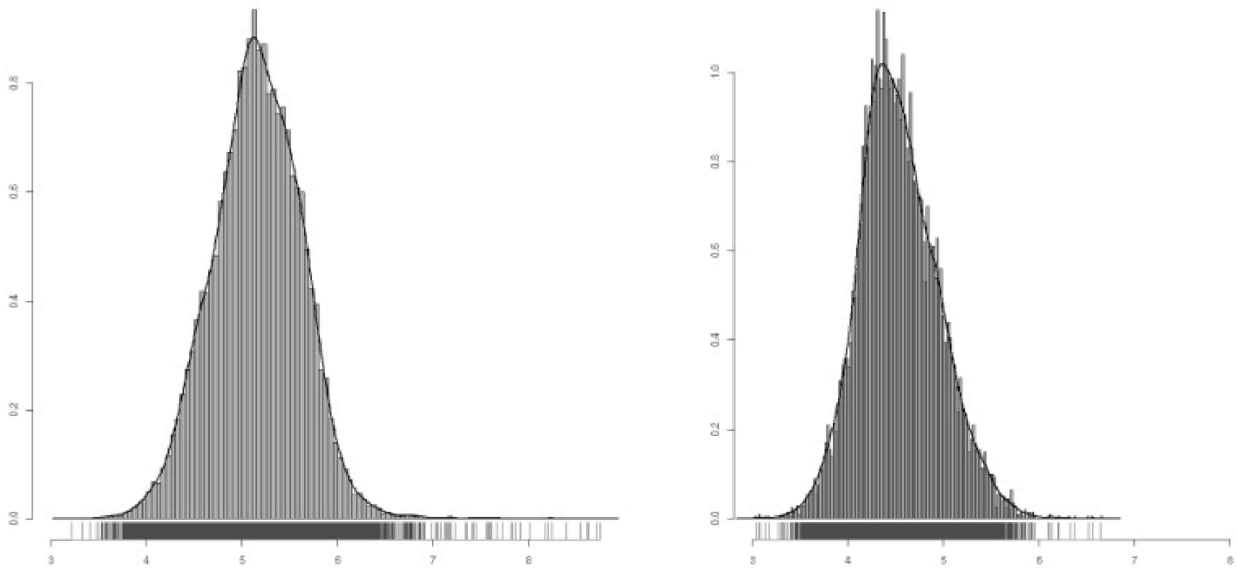


Unit B t_{wt} [°C] reheat steam temperature average I – 536.8 II – 539.6
Median I – 538.2 II – 539.64 Std, Dev. I – 5.11 II –1.89

Table 2: Results of statistical analysis of the principle performance parameters – reheat steam temperature – analysis from plan #1



O_2 [%] Concentration average I – 5.61 II – 4.9
Median I – 5.6 II – 4.7 Deviation I – 0.66 II – 0.77



O_2 [%] Concentration average I – 5.14 II – 4.58
Median I – 5.14 II – 4.56 Deviation I – 0.45 II – 0.42

Table 3: Results of statistical analysis of the principle performance parameters – O_2 concentration- analysis from plan #1

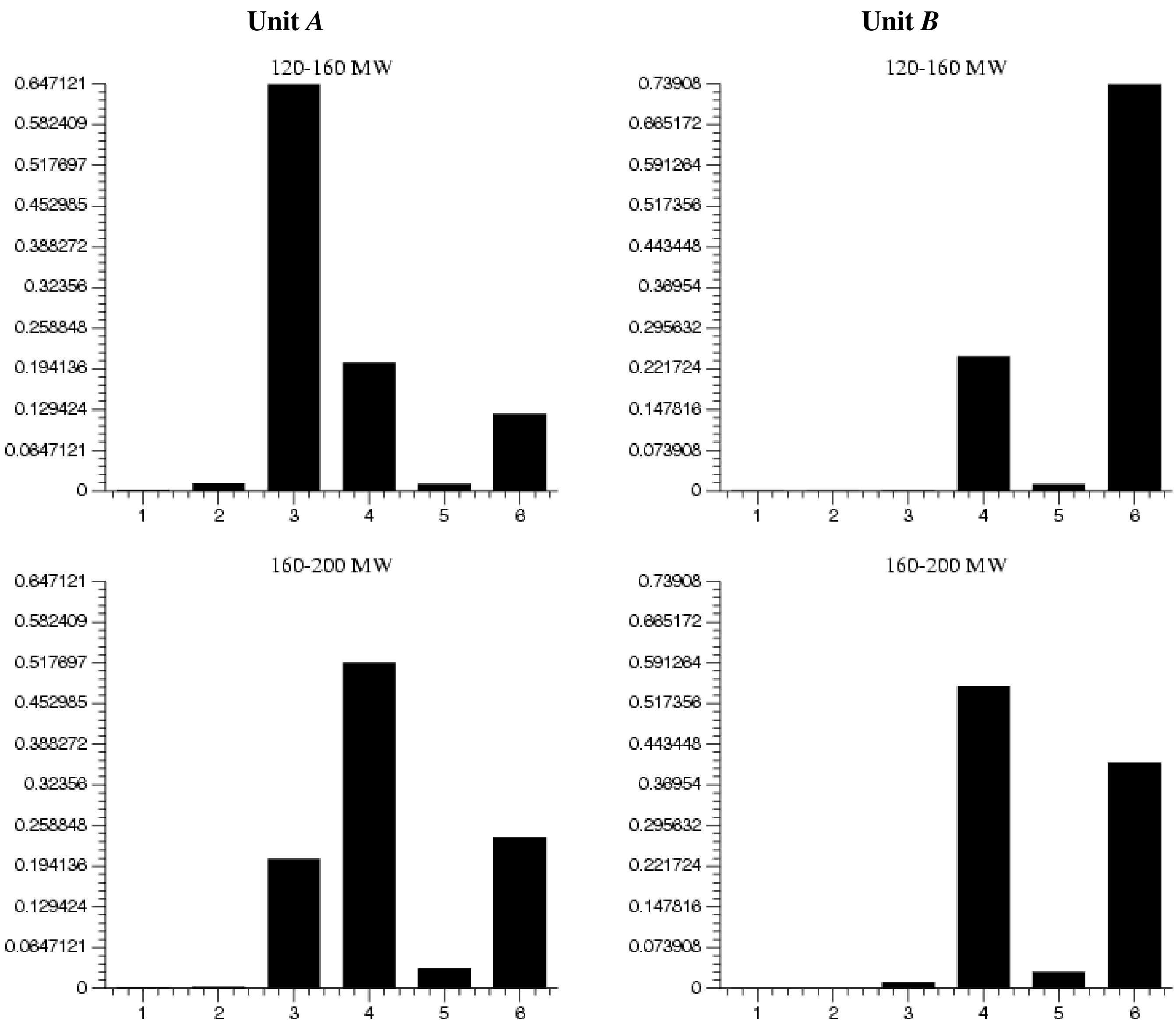


Figure 2: Analysis of results using the PCA method – analysis from plan #1

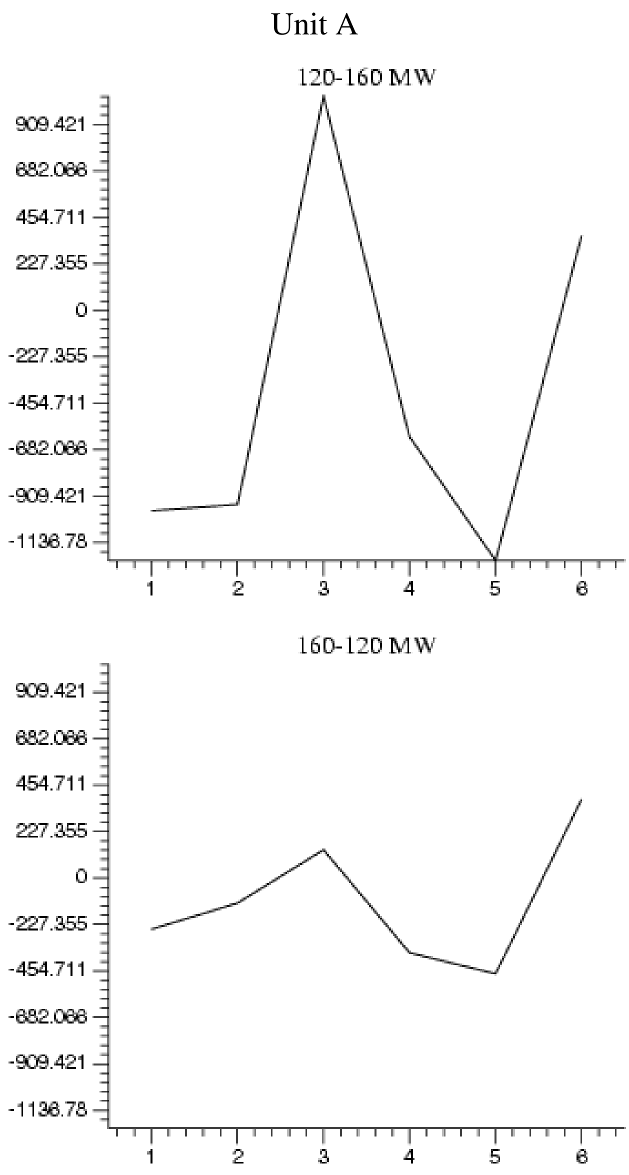


Figure 3: Linear regression – correlations of the basic parameters with regression models of heat rate qb- analysis from plan #1

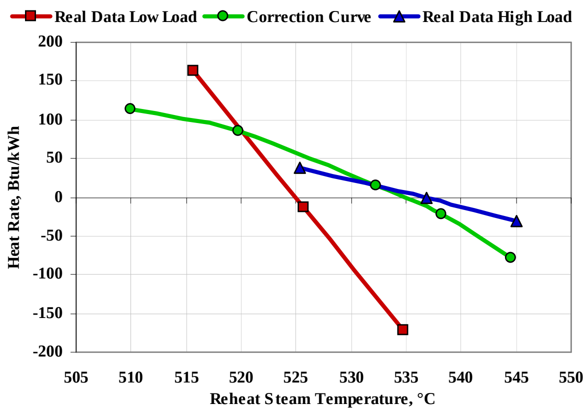


Figure 4: Heat Rate correction curve qb for reheat steam temperature and the corresponding values from statistical tests – analysis from plan #1

(manufacturer's data), obtaining the final dependencies shown in the figure below.

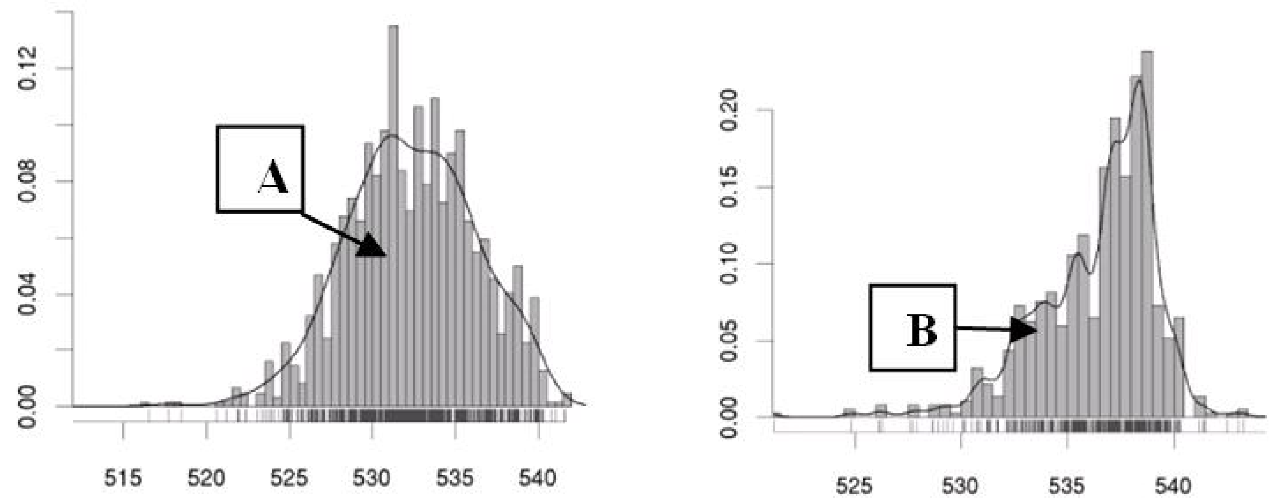
The blue line in the diagram shows the factory correction curve, the yellow line shows the appropriate values from linear regression for high power and the magenta line shows the same for low power. Comparing the data in the diagram shows that in a series of cases it is highly questionable to use correction curves. This is especially the case with evaluation of the operator's work (and the possible merit system), which does not take into account statistical analysis and can lead to significant inaccuracies.

- As regards calculation, the basic performance problem is the continually insufficient heating level of reheat steam at low powers caused by either poor tuning of the reheat steam control system or (more likely) construction faults (rebuilding of heated surfaces or change of fuel).

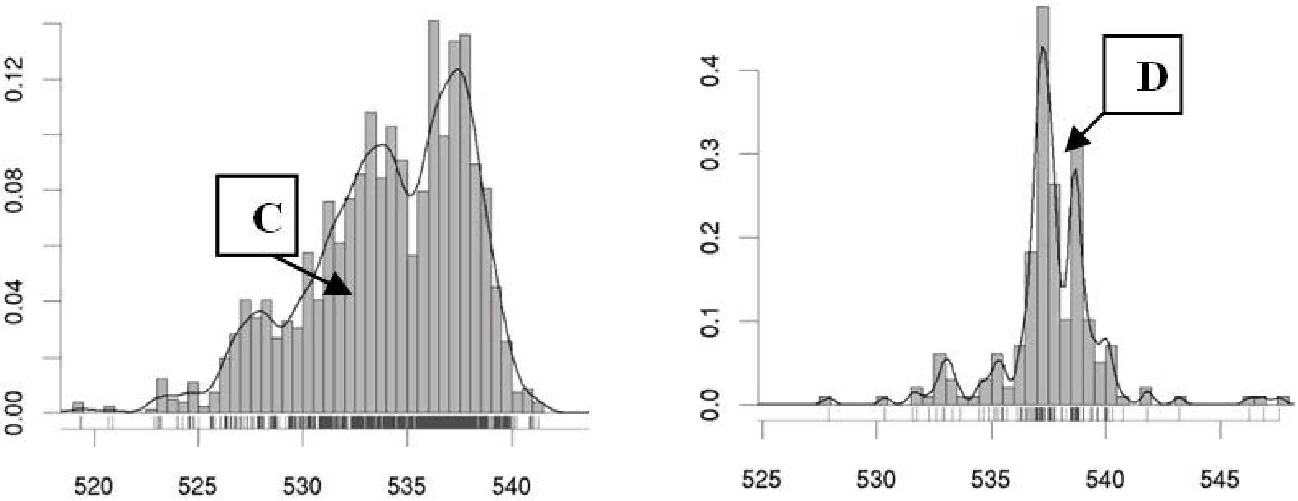
- In this case it is not possible to expect the process operator to be able to operate the unit at close to the nominal steam temperature (535 °C)

- In real operation of this unit, reheat steam temperature fluctuations cause much larger deviations in the heat rate (q_b) than are shown by the correction curve.

Similar type analyses were conducted for plan #2 – also twin 225 MW units with identical control systems.



Unit *C*, Main steam temp. [°C], Low load – left, High load – right



Unit *D*, Main steam temp. [°C], Low load – left, High load – right

Figure 5: Results of statistical analysis of the principle performance parameters – feedwater temperature – analysis from plan #2

When analyzing histograms we find that unit C experiences problems with main steam control (below nominal average temperature level with problems of set point quality (high deviation) at low loads (case ***A***) and high loads (case ***B***). In unit D, at high loads these problems do not exist (case ***D***) although at low loads average temperature level is lower than nominal and is accompanied by with poor control quality (case ***C***)

When analyzing feedwater temperature, problems may be observed with feedwater train operation in unit D (cases **3** and **4** – frequent lowering of feedwater temperature), contrary to proper operation as seen in unit C (cases **1** and **2**). Results from histogram analysis were confirmed with PCA and linear regression (with correlation) approaches.

6. Conclusion

The calculations of the performance monitoring method used to date, as used in their present scope, appear to have exceeded their limits. Modern performance control, having at its disposal tools in the form of constant efficiency calculations, automatic control systems integrated with archive systems and data analysis, is able to deliver a far more detailed and precise analysis of reasons for reductions in the quality of efficiency parameters. A particular cause for concern is the continued application of correction curves. What is postulated here is a modification through applying statistical analysis in a large scope and, as a result, systems of automatic reasoning. On the other hand, performance monitoring methods must be used alongside evaluation of other variable costs (emissions, energy trading, repairs, etc.) for a full market evaluation.

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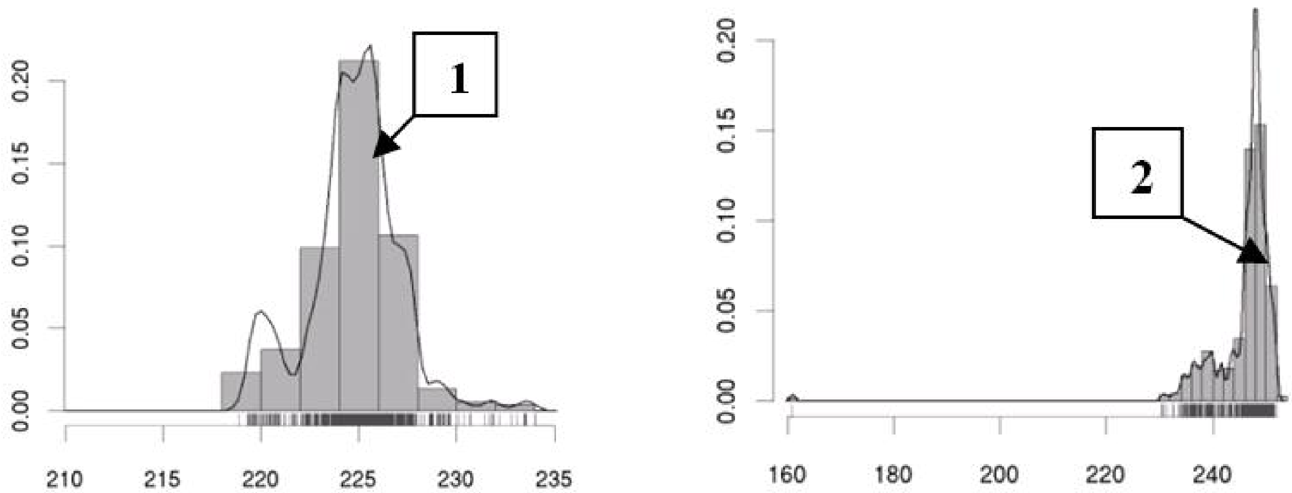
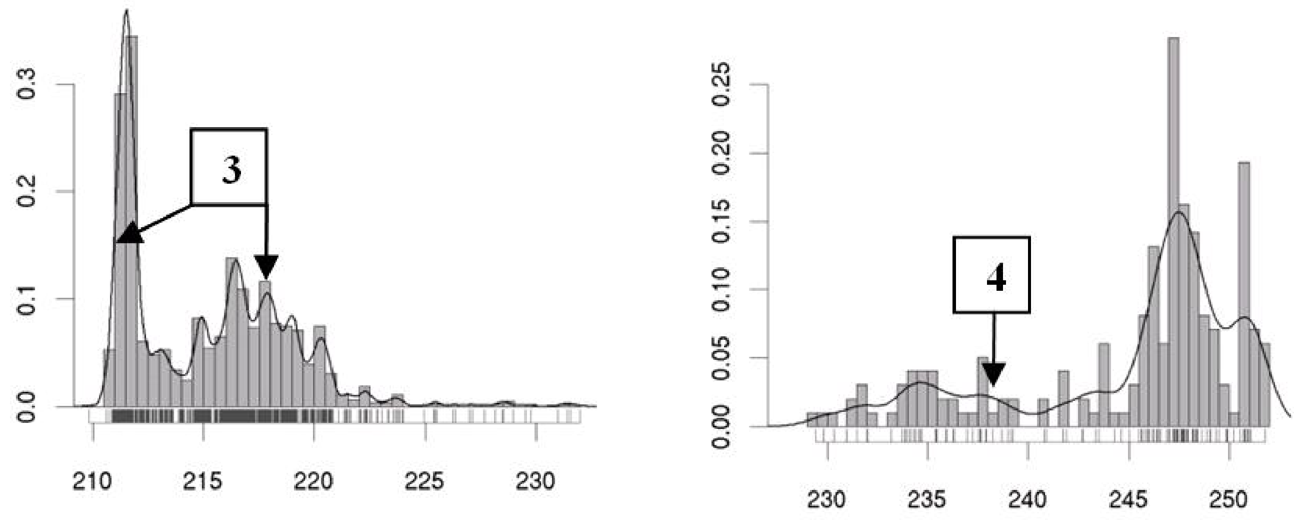


Unit *C*, Feedwater temp. [°C], Low load – left, High load – right



Unit *D*, Feedwater temp. [°C], Low load – left, High load – right

Figure 6: Results of statistical analysis of the principle performance parameters – main steam temperature – analysis from plan #2