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Ways of enhancing operational efficiency at power and CHP plants

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Abstract

Changes on the electricity market mean that variable costs of energy generation are under unprecedented scrutiny. Add concerns over emission limits, particularly CO_2 emissions, and a strong case emerges for enhancing generation efficiency Due to the construction parameters of existing plant and machinery, it is reasonable to assume that increased efficiency might be achieved by identifying optimal load distribution among generation units and rapid detection of elements whose technical condition may reduce efficiency. In both cases comprehensive knowledge about the attributes of existing equipment is required. This article presents methods to boost generation efficiency at current, functioning units.

1. Introduction

Power plants are managed to produce the best commercial result. Central to this objective are two elements: optimal load of the facility and the optimal operating parameters to achieve minimum wear and tear. To this end technical data is required to inform and evaluate the work of plant operators. This article presents the typical method of assessment plus various options offered by modern control systems.

2. Disadvantages of the current technical operationcontrol method (Polish: TKE)

The TKE (Technical Operation Control) method that is currently used in power and CHP plants was developed more than 30 years ago and was compliant with American and Western European power plants operation control standards in the 60s and 70s. Use of the TKE method is becoming increasingly controversial due to 2 basic issues: IT advancements that enable extensive use of digital automation systems plus systemic changes in the energy market. Moreover, doubts have arisen over the accuracy and utility of the TKE approach.

Typical TKE methodology is used in most power plants in Poland. It is based on calculating the unit fuel chemical energy consumption (PN-93 M-35500 and engineering calculations) and determining the measurable losses – unitary deviation in the fuel chemical energy consumption qbcompared to the expected value (nominal or specified in the last maintenance check report) – which results from unit operation on parameters different from nominal [1, 2]. Basic parameters (variables x_i), whose influence on the unit consumption is generally taken into consideration, are (the first five parameters correspond with the main correction parameters of unit heat consumption by a turbine according to PN-71 M 35520 and PN IEC 45-1):

1. Live steam pressure

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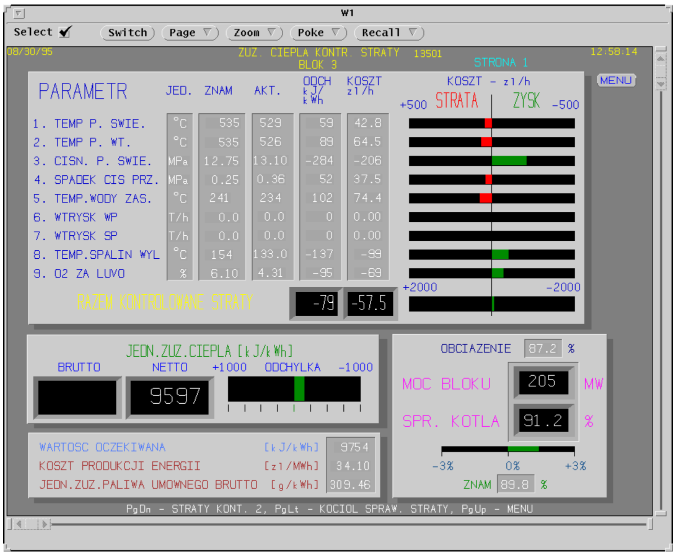


Figure 1: Typical operators' screen presenting the results of current calculations for operational control at the DCS operating station

2. Live steam temperature
3. Pressure drop in the superheater
4. Secondary superheated steam temp.
5. Pressure in the condenser
6. Supplying water temperature
7. Oxygen in flue gases
8. Flue gases temperature

The amount of controlled parameters was extended more than once [1] but in keeping with the theoretical basis of the method. Unitary deviation in the heat consumption q_b[kJ/kWh] (fuel chemical energy) is often calculated and presented in PLN/h so to present data in a clearer form. Systems based on TKE or similar methodology were introduced into almost all power plants at the same time as updates to the IT and automation systems. Generally, deviation calculations are made online and the results presented on the operators' monitors.

The TKE method, even though definitely needed and effective, has a number of weak points of which we should be aware. After so many years it is possible to assess the results of the operational parameters of a power unit more critically and to perform a deeper analysis. The basic problems connected with use of the TKE methodology are:

- **Reference values** – currently most deviations and losses are calculated and monitored according to 'reference values' – usually nominal values supplied by the manufacturer. For machinery with 10-20 years of active service behind it and numerous upgrades, the nominal values do not reflect the real features of the equipment;
- **Correction curves for determining controlled (measurable) losses** – in the TKE method, the influence of deviation on the operation parameters (temperature, pressure, etc.) in comparison to the reference values (design, available, etc.) is specified mainly by using the correction curves issued by the manufacturers. The curves are drawn with the assumption that the operational parameters of a power unit are independent, which allows one to separate out the influences according to the formula:

$$q_b = q_b\left(P^o\right) + \left(\frac{\partial q_b}{\partial p_o}\right)\left(p_o - p_o^o\right) + \left(\frac{\partial q_b}{\partial T_o}\right)\left(T_o - T_o^o\right) + \ldots \qquad (1)$$

where P – power of a unit, p_o– live steam pressure, T_o – live steam temperature, and the upper "o" index corresponds to the operational conditions for reference parameters.

In reality there is a strong relation between those parameters (they are implicit, in example in the case of the formula for the steam flow capacity of a turbine). In simplistic terms, in normal operation, it is impossible to change one parameter without altering several others. Additionally, relations between those parameters do not depend only on thermodynamic parameters (balance) but also on the functioning of the unit's automation system. In other words, alteration of one of the main operational parameters of a power unit will, in practice, force the automatic regulation systems to change the unit's operation state (modifying other parameters as well). This is the reason why deviations determined by correction curves have no place in practical applications. For example, if we determine the instantaneous heat consumption deviations for a set of principal parameters (and obtain a large negative deviation for one of them that resulted from the difference between actual and nominal (reference) values), then if the difference is removed (changing the parameter to the nominal-reference value, hence reducing the deviation), all the other parameters will remain unchanged (!). We will in fact obtain a totally different set of parameters that will be equal to the differences between them and the reference values and, consequently, different values of measurable deviations.

Theoretical divagations lead to the following two practical questions (and attempts to answer them) [3, 4]:

- **What are the currently achievable parameters of a power unit?** Units built in 60s, 70s and 80s have undergone multiple upgrades. The fuel combusted in some has significantly different parameters than projected. The principal devices (boiler, turbine) were modernized and reconstructed. In practice the outcome is that we are looking at a totally different object than was specified in the project. The effect is such that in the operational control analysis according to the TKE method large deviations appear (both positive and losses) that cannot under be eliminated by the process operator any circumstances, as they result from long-lasting changes in the unit operation parameters. In this case, determination of deviations compared to the project data seems meaningless and impractical. Instead, it is expedient to evaluate the losses (or possibilities of operational improvement) based on the mean values (obtained during long-term operation) or the best gathered during operational time ("best practices").

- **Which operation losses are the most crucial and which can truly be reduced?** In practice it is crucial to make a real evaluation of the q_b deviation (and the costs it generates). It seems sensible to search for a method that unequivocally identifies losses (deviations) that can be reduced as well as the real influence of process parameters on the operational efficiency of a power unit (considering the real characteristics of the unit, which include the reaction of the automation systems).

3. Proposed changes in the operation control algorithms

As power units are equipped with digital automation systems, the calculations of q_b are performed continuously during operation, so we have at our disposal a comprehensive amount of data to feed potentially incomparable statistical analysis. Assuming, for instance, that in an online (current time) operation analysis we are aware of the problems connected with measurements and calculations and the measured data is properly treated in order to eliminate measurement errors and filter the non-stationary state of the unit, etc. Then, using the measurements we obtain a large, reliable database of calculated data on unit heat consumption for different operational states of the unit. The collected data on unit heat consumption then undergoes:

- **basic statistical analysis** with determination of statistic measures (descriptive statistics) and histograms [3],
- **PCA – Principle Component Analysis** [3].

A linear model of unit heat consumption (linear regression model) regarding the operational parameters x_i **should be built** and the correlation coefficients between the variables x_i and q_b investigated.

The main goal of the statistical analysis is to plot histograms and determine the mean values of process parameters and to compare them with the reference values. That allows one to check the extent to which the real operation parameters (mean and most common values) tally with the reference values (nominal).

Owing to the capacity of current automation systems it is possible to archive data practically from the whole operation time and, hence, perform unlimited data analysis. In order to determine the base reference operational parameters it is advised to aggregate the data in the function of unit productivity (steam flow, power). The computed examples below present the results for two arbitrary power ranges: 120--160 MW (low power) and 160--200 MW (high power). They correspond to the typical operation regimes. In the developed form a function can be obtained for any parameters depending on the productivity (power) of the unit.

The Principal Component Analysis is a method in which a linear transformation is determined. It transforms the initial variables x_i into new variables (called main components) that are not correlated. In this transformation the most important information regarding the original variables is retained. In particular, the first component shows the direction of the largest spread of analyzed variables. With regard to a specific operation data analysis the PCA enables:

- determination of new variables (imaginary), where each of them is a combination of basic process parameters having no correlation with the others,
- determination of the first PCA component and, through analysis of it, identification of the parameters with the greatest spread.

This analysis informs the empirical dependence $q_b = f(x_1, \ldots, x_n)$.

The linear regression model is the simplest empirical approximation of the unit heat consumption based on basic process parameters. Assuming it is possible to construct such a model with sufficient accuracy, the next step should be determination of correlations between the basic parameters, which results directly in determination of the impact on the unit heat consumption caused by those parameters. Naturally, the linear regression model may be subsequently modified (non-linear models, neural networks, fuzzy networks, etc.) in order to improve mappingaccuracy.

In order to exemplify this, the results of a statistical analysis made for two similar 225 MW units of identical design and having twin automation systems are presented below. The data used for analysis (properly averaged and aggregated in appropriate unit power ranges) was obtained from current operation calculations within a 12-month timeframe. The outcomes of the analyses performed for both units are presented on Figures 2, 3 and 4 [3]. Histograms and principal statistical measures for proper power ranges for unitary heat consumption, live steam temperature and vacuum in the condenser are presented.

The analysis results in the following conclusions:

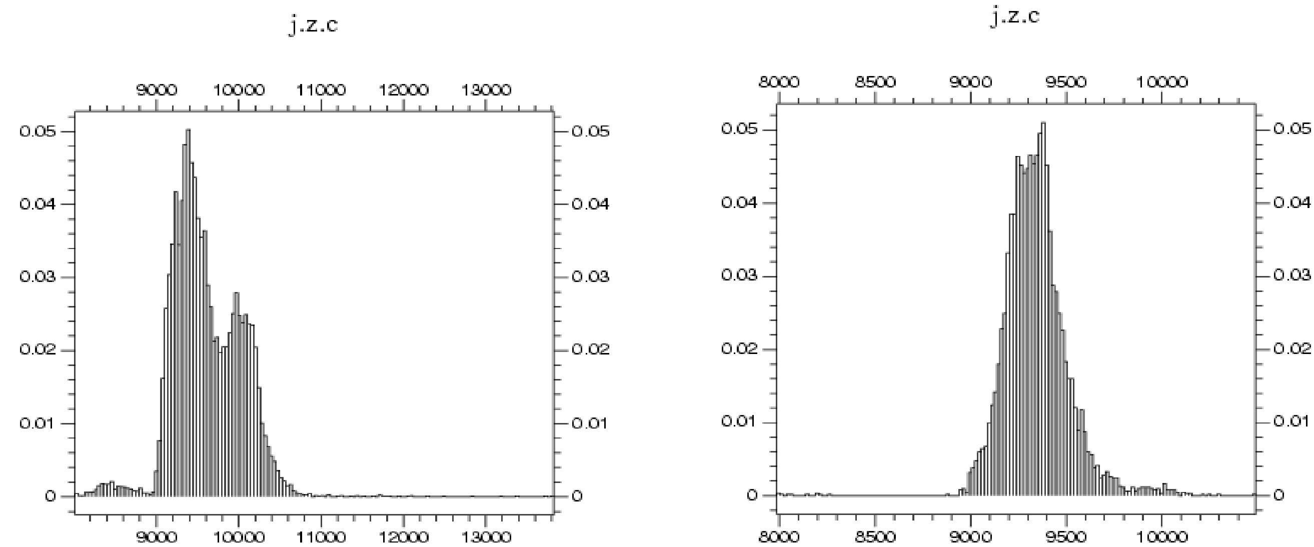
- even twin power units have different operation characteristics and different histograms of basic parameters
- in many cases the real process values (obtained during operation) differ significantly from the nominal values (often assumed as reference values) and, additionally, may be significantly different depending on the unit's power range (output of the boiler) – for example, the temperature of secondary steam for unit A at low loads has an average value of 526°C and substantial inconstancy (standard deviation) – showing the existence of areas of insufficient heating
- observation of variability of regulated parameters (standard deviation) also enables one to draw conclusions as to the level of synchronization of the automation systems
- the main operation problem of analyzed units is persistently insufficient heating of secondary steam for low powers, which is caused either by bad synchronization of secondary steam regulation system or, more probably, by structural reasons (reconstruction of heating surfaces or change of fuel); the features of both condensers are also important.

In this particular case the process operator cannot be expected to be able to alter the conditions to the degree required to operate the unit at close to the nominal steam temperature (535°C) in order to decrease unit fuel consumption.

The PCA analysis is an attempt to identify the most varying process parameters by transforming them into independent (not correlated) parameters. The first main component for both units was presented in Figure 5 (each of the numbers represent contribution of the process parameter to the main component).

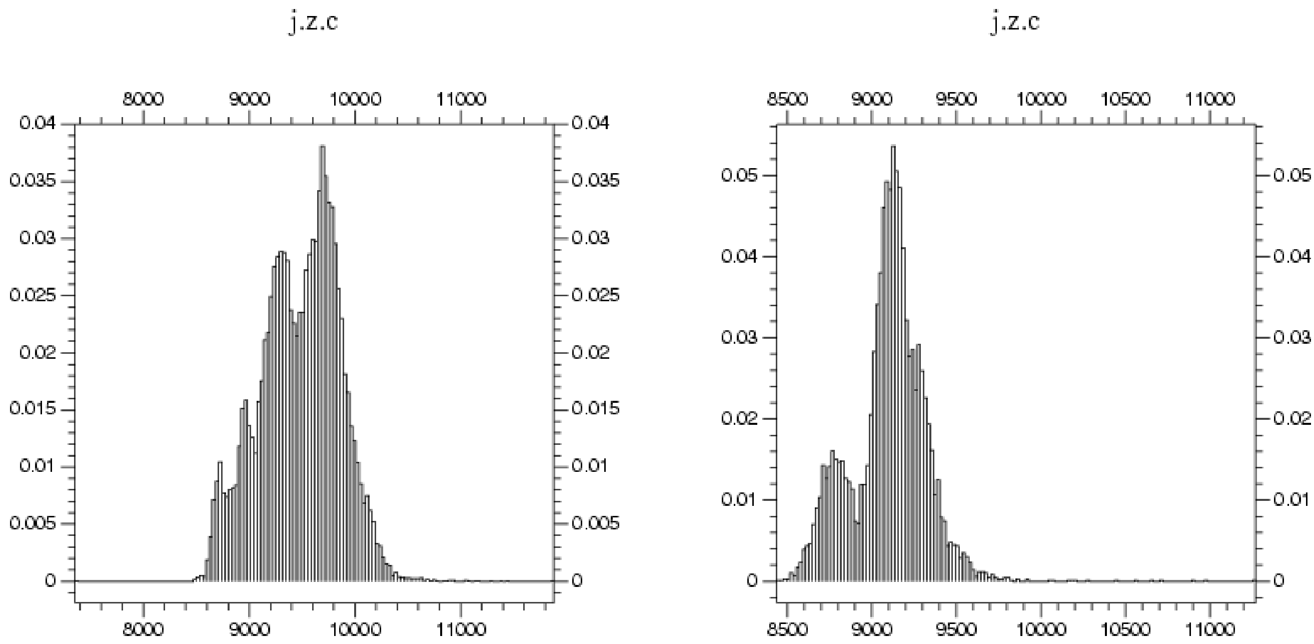
The PCA may enable rapid identification of parameters causing the largest changes of the unit heat consumption. In this particular example, it is the secondary superheated steam temperature for unit A at low power (variable no. 3). For unit B, the large spread variables are: the pressure drop in the superheater and the pressure in the condenser (variability due to seasonality), so the hypothesis that there are

Unit A Low Power (I) 120--160 MW   Unit A High Power (II) 160--200 MW



Unit A, q_b, kJ/kWh; Mean I – 8850 II – 8630 Median I – 8840 II – 8638 Deviation I – 397 II – 174

Unit B Low Power (I) 120--160 MW   Unit B High Power (II) 160--200 MW

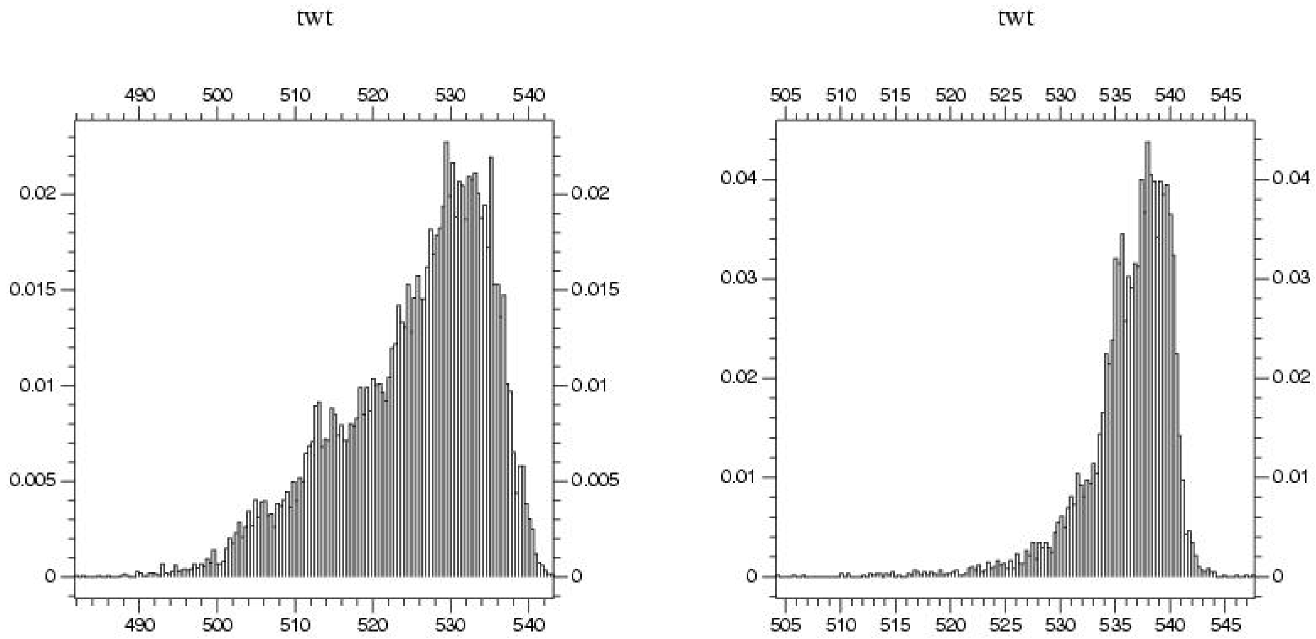


Unit B, q_b, kJ/kWh; Mean I – 8756 II – 8107 Median I – 8787 II – 8425 Deviation I – 353 II – 214

Figure 2: Histograms of unit heat consumption

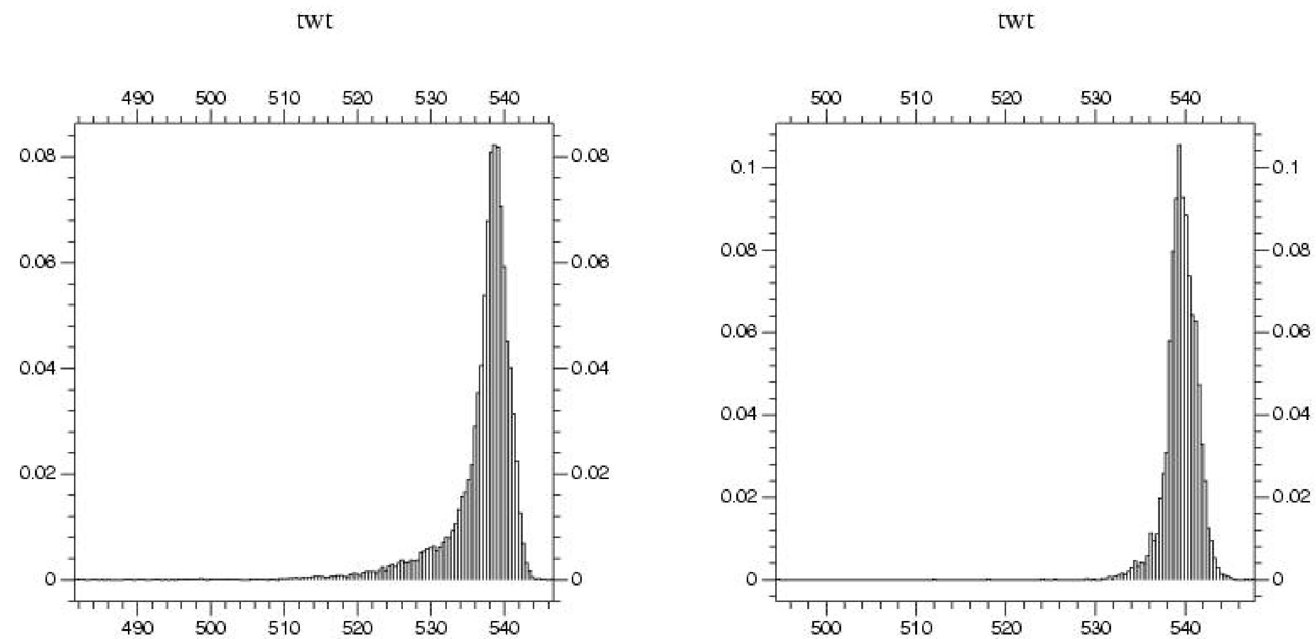
Secondary steam temperature

Unit A Low Power (I) 120--160 MW   Unit A High Power (II) 160--200 MW



T_{wt}, °C; Mean I – 525.2 II – 536.45 Median I – 536.7 II – 538 Deviation I – 9.55 II – 4

Unit B Low Power (I) 120–160 MW   Unit B High Power (II) 160–200 MW

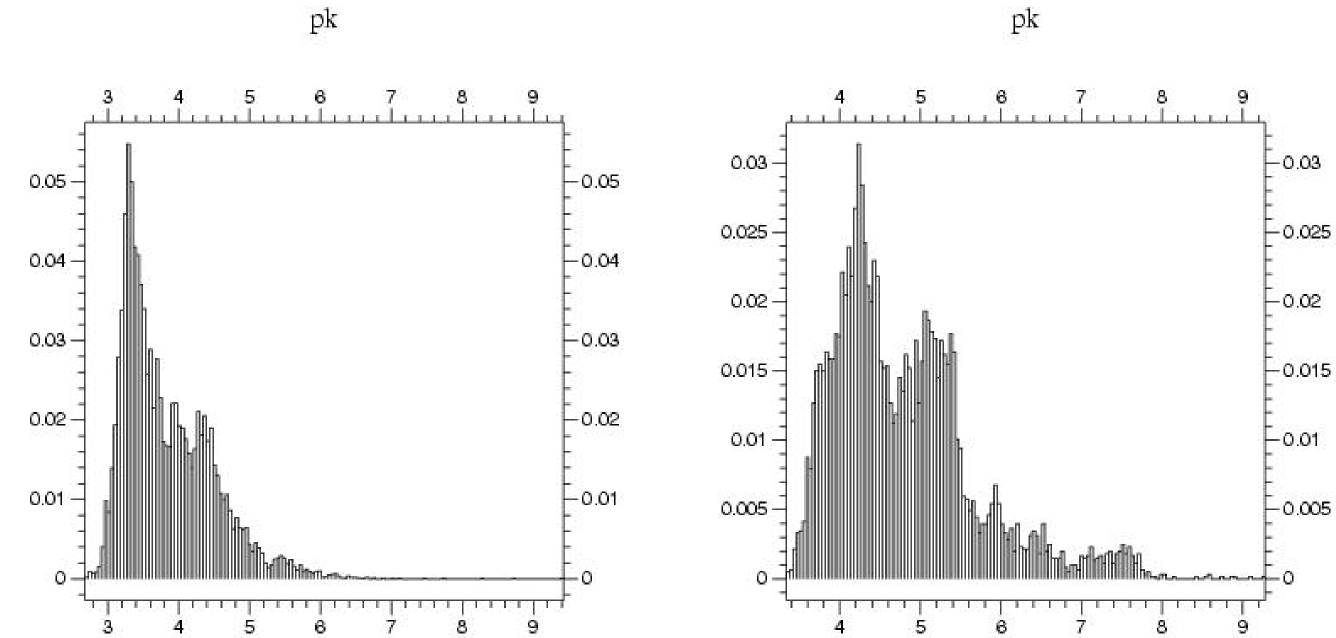


T_{wt}, °C; Mean I – 536.8 II – 539.6 Median I – 538.2 II – 539.64 Deviation I – 5.11 II – 1.89

Figure 3: Histograms of temperature for secondary superheated steam

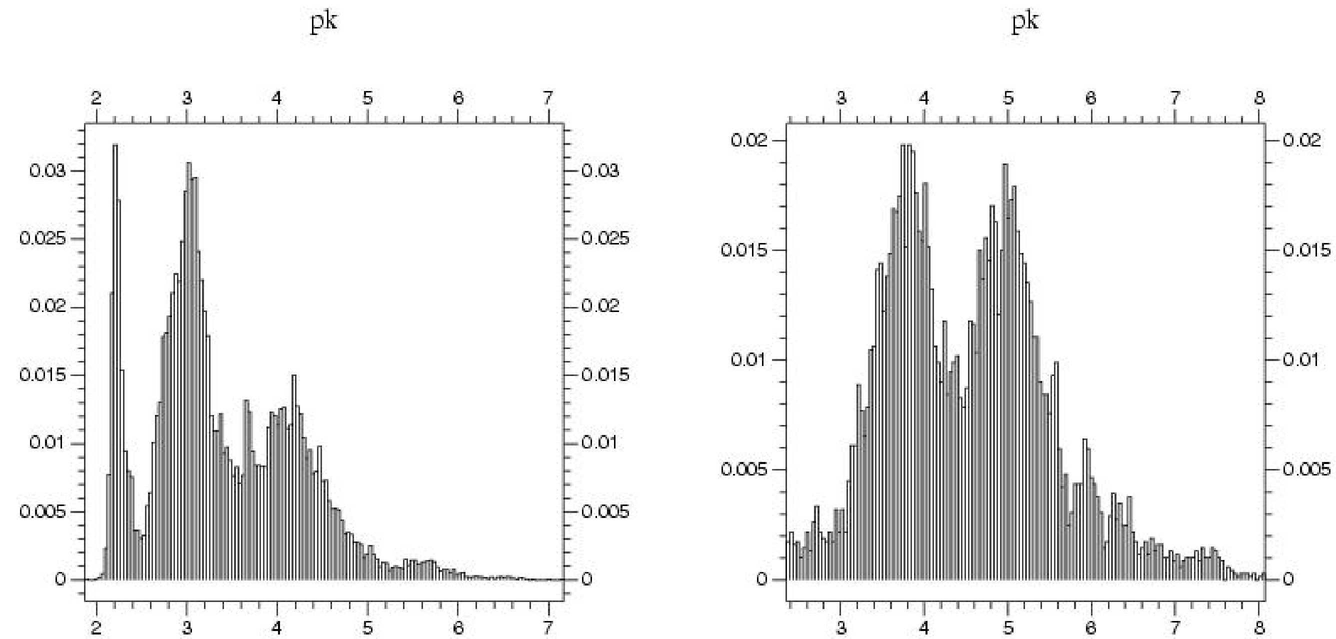
Pressure in the condenser

Unit A Low Power (I) 120–160 MW | Unit A High Power (II) 160--200 MW



p_k, kPa; Mean I – 3.83 II – 4.79 Median I – 3.66 II – 4.59 Deviation I – 0.63 II – 0.88

Unit B Low Power (I) 120–160 MW | Unit B High Power (II) 160--200 MW



p_k, kPa; Mean I – 3.38 II – 4.53 Median I – 3.17 II – 4.5 Deviation I – 0.82 II – 0.99

Figure 4: Histograms of pressure in the condenser

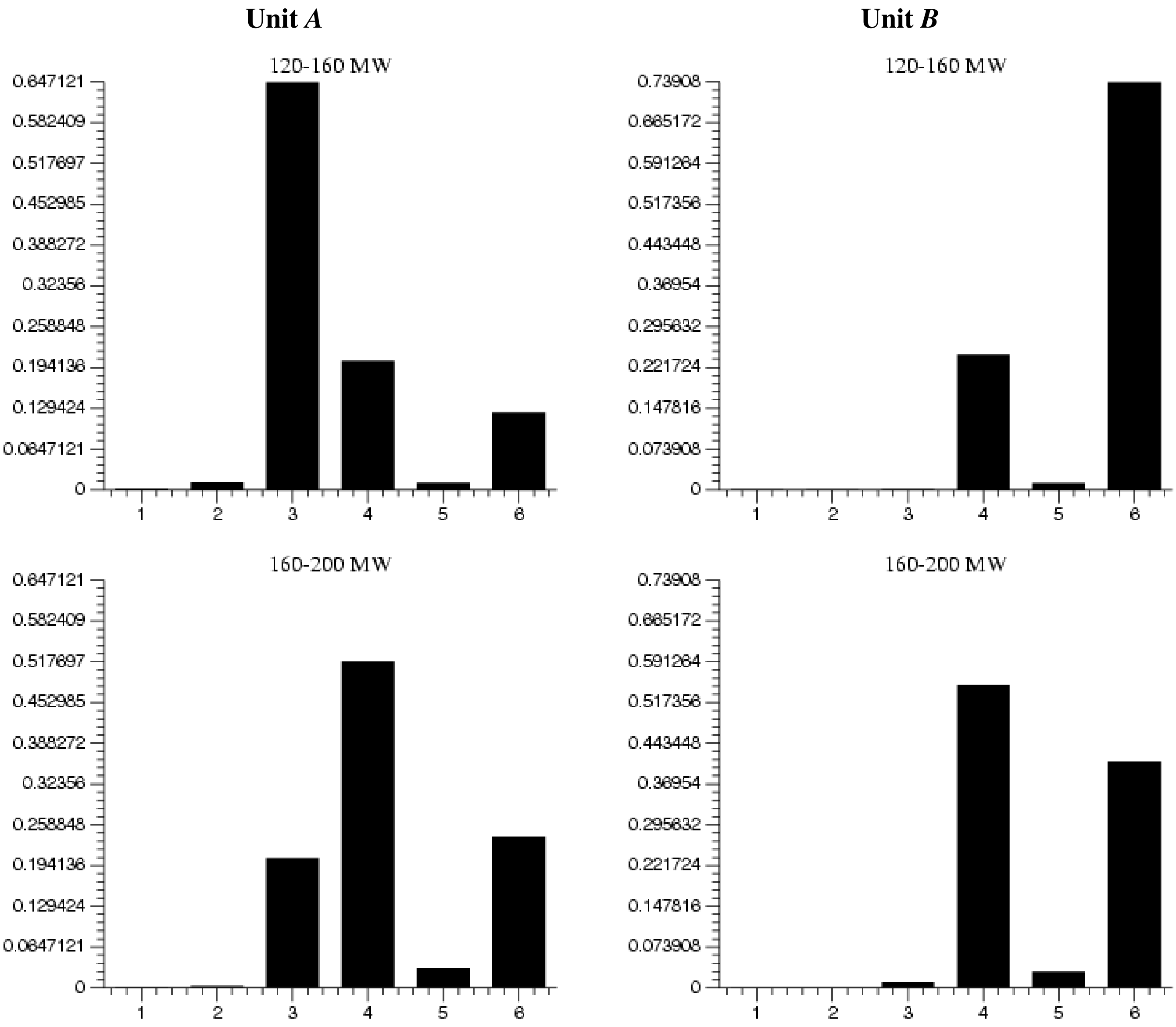


Figure 5: Results of data analysis by the PCA method; 1 – live steam pressure, 2 – live steam temperature, 3 – pressure drop in the superheater, 4 – temperature of secondary superheated steam, 5 – pressure in the condenser, 6 – temperature of supply water, 7 – amount of oxygen in flue gases, 8 – flue gases temperature

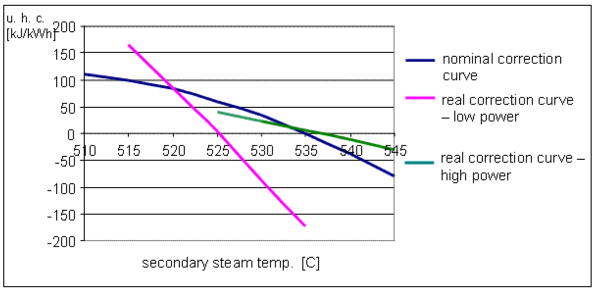


Figure 6: Correction curve $\triangle q_b$ for secondary steam temperature and corresponding curves resulting from statistical analysis of a real unit

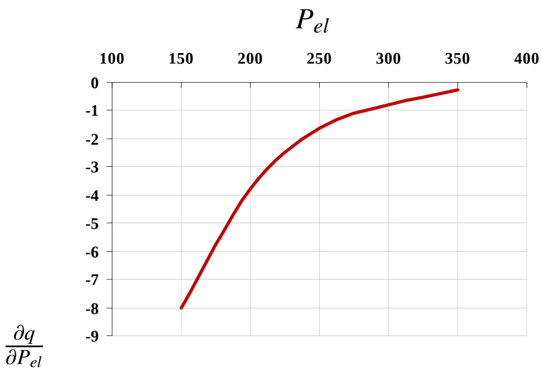


Figure 7: Derivative of unit chemical energy consumption of a fuel in the function of the unit power

no significant operational problems with this unit can be formulated.

Regressive analysis can be used to determine the correction curves that represent the real condition of the unit. An example of such a curve for secondary superheated steam and its comparison with the nominal curve is presented in Figure 6. In the real operational practice of the unit, the variations of secondary steam at low powers cause considerably greater deviations q_b than obtained from the correction curve. Comparing the data presented in the graph it is clear that in many cases the usefulness of those curves is highly debatable. In particular, any assessment of an operator's work (and presumptive premium system) that does not take statistical analysis into account may lead to significant inaccuracies.

4. Load distribution among devices

ELD (Economic Load Distribution) resolved the issue of optimal load distribution among several devices in operation over twenty years ago. In systemic multiple-unit power plants the ELD problem is solved by optimal load distribution among the units. The traditional ELD method uses the characteristics of the unit chemical energy consumption of the fuel in the function of the turboset power (Figure 7).

If there is need for increase in the total power of several units equal to $\triangle P$, then, according to the ELD algorithm, the power of the unit for which the derivative $\frac{\partial q}{\partial P_{el}}$ has the highest value.

Currently, at the level of the power plant the load distribution is not optimized and existing "group regulators" have been closed down or are not used. The characteristics of theoretically identical units may differ significantly in practice, particularly at low loads (Figure 8). The characteristics of variable costs should form the base for optimization (Figure 9).

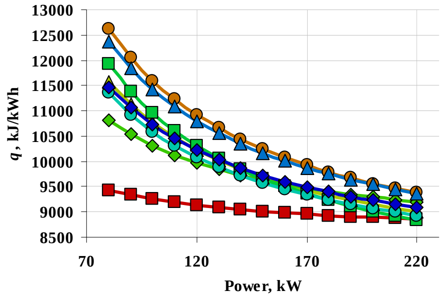


Figure 8: Characteristics of unit heat consumption for "identical" units installed in the same power plant

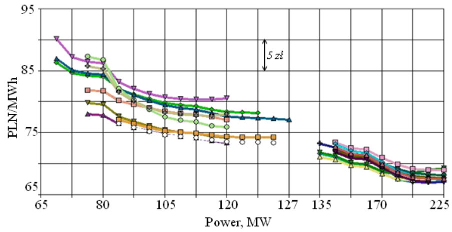


Figure 9: Different variable costs (excluding CO_2 costs) for identical units

If the differences of variable costs of generation sometimes exceed PLN10/MWh, then the effects of optimal load distribution will be considerable.

Optimization of load distribution in a CHP plant is much more difficult, particularly in an industrial plant, but the effects could be huge. Exemplary optimization results, i.e. the timeline of the total power generated in a CHP plant is presented in Figure 10 for two load distributions – optimal and "by guess".

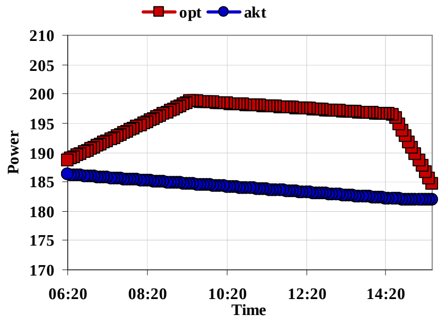


Figure 10: The track of power changes in a commercial CHP plant for normally applied (act) and optimal (opt) load distributions

5. Conclusions

The presented method can significantly improve the quality of control in power plants. Historical data can be used to provide detailed insight into the work of individual units. The PCA method was proposed to activate the process control and optimization of plant operation. Optimization of plant operation should be based on current actual characteristics. The proposed methods could deliver significant improvements in the quality of these processes.

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