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Fault Detection in Electric Power Systems Based on Control Charts

Emilija Kisić[1], Vera Petrović[1], Miroslav Jakovljević[2], Željko Đurović[3]

Abstract: This paper analyzes the control system of the combustion process and protection from explosions in the boiler furnace of thermal power plant using the techniques of control charts. The data from old and newly introduced system for measuring under-pressure differences in boiler furnace at unit B2, TE Nikola Tesla (TENT) Obrenovac, were analyzed. The signal of undepressure diference is used for boiler protection function in thermal power plant TENT B. The results that confirm the advantages of the newly introduced system of measurements are presented. A detailed discussion about the benefits and the shortcomings of the control charts application in industrial processes are given in the paper.

Keywords: Control chart, Statistical process control, Fault detection, Under-pressure difference in boiler furnace.

1 Introduction

Process control and monitoring are becoming essential tasks in nowadays industry. Today, all processes are automatized and they contain a lot of sensors and actuators. Because of that, the control of these processes is sometimes very difficult. There are two principal approaches to perform the process control, namely, data driven techniques and analytical techniques [3]. In theory, the analytical technique is the better approach. It is based on analytical (physical) model of the system and permits to simulate the system. Though, at each instant, the theoretical value of each sensor can be known for the normal operating state of the system. As a consequence, it is relatively easy to see if the real process values are similar to the theoretical values. But, the major drawback of this approach is the fact that it requires detailed models of the process. An effective detailed model can be very difficult, time consuming and expensive to obtain, particularly for large scale systems with many variables. The data-driven

[1]School of Electrical Engineering and Computer Science of Applied Studies, Vojvode Stepe 283, Belgrade, Serbia; E-mails: emilija.kisic@viser.edu.rs, vera.petrovic@viser.edu.rs
[2]CE, "Thermal Power Plants Nikola Tesla" d.o.o, TENT B, Bogoljuba Uroševića 44, Obrenovac, Serbia; E-mail: miroslav.jakovljevic@tent.rs
[3]School of Electrical Engineering, University of Belgrade, Bulevar Kralja Aleksandra 73, Belgrade, Serbia; E-mail: zdjurovic@etf.bg.ac.rs

approaches are a family of different techniques based on the analysis of the real data extracted from the process. These methods are based on rigorous statistical development of the process data. In this paper we will work in the data-driven monitoring framework.

Many data-driven techniques for the fault detection can be found in the literature: univariate statistical process control [1], multivariate statistical process control [2], and some PCA (Principal Component Analysis) based techniques [5, 6]. Other important approaches are PLS (Projection to Latent Structures) based approaches [7]. These fault detection techniques are able to detect a fault (disturbance) in a univariate and multivariate processes. The fault diagnosis procedure can also be seen as a classification task. Combination of multivariate statistical process control and Bayesian network as classifier can be found in literature [4, 8]. In this article we will describe implementation of univariate statistical process control in electric power system.

Statistical process control (SPC) is a powerful collection of problem-solving tools useful in achieving process stability and improving capability through the reduction of variability. SPC can be applied to *any* process. It has seven major tools, but the *control chart* is the most technically sophisticated. It was developed in the 1920. by Walter A. Shewhart [9] of the Bell Telephone Laboratories. Since then many types of control charts were developed and univariate SPC is extended to multivariate SPC when there is need for monitoring more than one variable. Control charts have had long history of use in industries. There are many reasons for their popularity. Control charts are a proven technique for improving productivity, as they are effective in defect prevention, they prevent unnecessary process adjustment, they also provide diagnostic information and they provide information about process capability. Modern computer technology has made it easy to implement control charts in any type of process, as data collection and analysis can be performed on a microcomputer or a local area network terminal in real time.

The main purpose of the control chart is to improve the process. In practice it is generally found that most processes work out of statistical control. Routine and careful use of control charts may help in successful identification of failures. If the causes of failures can be eliminated, variability will be reduced, and consequently the process will be improved [1].

The application of control chart techniques on real process in thermal power plant is described in this article. The old and newly introduced system for measuring under-pressure differences in boiler furnace at unit B2, Thermal Power Plants Nikola Tesla, Obrenovac, Serbia, were analyzed. The main goal of this analysis is to confirm advantages of the newly introduced system in regard to old system of measurement. In electric power systems the most important task is the increase of efficiency and reliability. Therefore, the analysis of the control system of the combustion process and protection from explosions in the boiler furnace with control charts aims to help in improving the whole system and make it more reliable.

This paper is structured as follows: in the next section we present the general theory of control charts. In Section 3 the control system of the combustion process and the protection from explosions in the boiler furnaces of thermal power plant is introduced, in details with its most important features. In Section 4 we present the application of control charts on the old and newly introduced system for measuring under-pressure differences in boiler furnace at various altitudes, and experimental results are presented. In Section 5 the conclusion and a short discussion about the advantageous and the shortcomings of the application of control charts in industrial processes and possible solutions to problems encountered are presented.

2 General Theory of Control Charts

The control chart is a statistical tool for fault detection in the system. Control charts make a clear difference between changes that are result of numerous, always present immeasurable disturbances in the process and changes that are the result of system fault. Generally speaking, control charts present graphical display of regular, e.g., irregular operation mode of process during time.

In any production process, regardless of how well it is designed and maintained, a certain amount of inherent or natural variability will always exist. This natural variability or "background noise" is the cumulative effect of many small, essentially unavoidable causes. In the framework of statistical quality control, a system that has this natural variability is often called a "stable system of *common causes*". A process that is operating with only common causes of variation is said to be *in statistical control*. In other words, the common causes are an inherent part of the process. Other kinds of variability may occasionally be present in the output of the process. Such variability is generally large when compared to the background noise, and it usually represents an unacceptable level of process performance. We refer to these sources of variability that are not part of the chance cause pattern as "*special causes*". A process that is operating in the presence of special causes is said to be *out of control*.

The control chart is a graphical display of a quality characteristic that has been measured or computed from a sample versus the sample number or time. A typical control chart contains a center line that represents the average value of the quality characteristic corresponding to the in-control state, e.g. only common causes are present. Two other horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL), are also shown on the chart. These control limits are chosen so that if the process is in control, nearly all of the sample points will fall between them. It is customary to connect the sample points on the control chart with straight-line segments, so that it is easier to visualize how the sequence of points has evolved over time. On Fig. 1 typical control chart is shown.

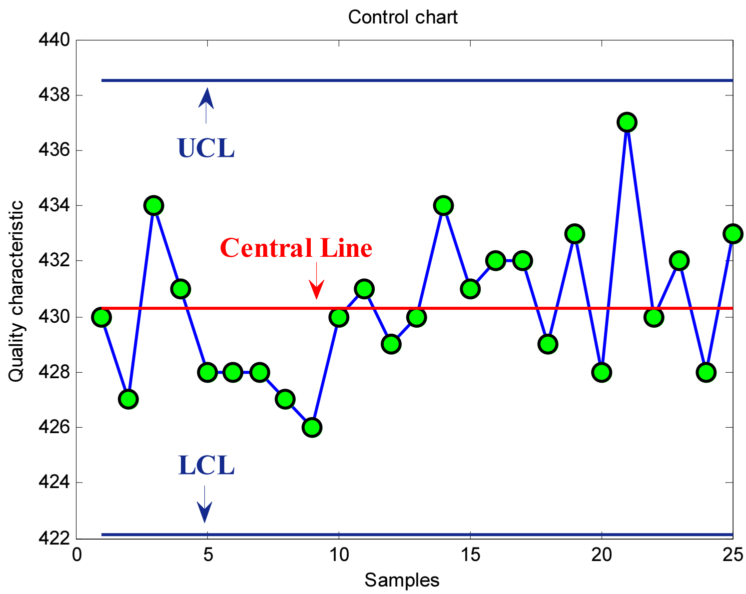


Fig. 1 – *Typical control chart.*

Even if all the points fall inside the control limits, if they behave a systematic or nonrandom manner, then this could be an indication that the process is out of control. If the process is in control, all the plotted points should have an essentially random pattern.

There is a close connection between control charts and *hypothesis testing*. The control chart is a test of the hypothesis that the process is in a state of statistical control. A point plotting within the control limits is equivalent to failing to reject the hypothesis of statistical control. One place where the hypothesis testing framework is useful is in analyzing the performance of a control chart. For example, we may think of the probability of type I error of the control chart (concluding the process is out of control when it is really in control) and the probability of type II error of the control chart (concluding the process is in control when it is really out of control).

We now may give a general model for a control chart. Let w be a sample statistic that measures some quality characteristic of interest, and suppose that the mean of w is μ_w and the standard deviation of w is σ_w. Then the center line, the upper control limit, and the lower control limit become

$$UCL = \mu_w + L\sigma_w,$$
$$CL = \mu_w, \tag{1}$$
$$LCL = \mu_w - L\sigma_w,$$

where L is the “distance” of the control limits from the center line, expressed in standard deviation units. This general theory of control charts was first proposed by Walter A. Shewhart, and control charts developed according to these principles are often called Shewhart control charts.

Specifying the control limits is one of the critical decisions that must be made in designing a control chart. By moving the control limits further from the center line, we decrease the risk of a type I error. However, widening the control limits will increase the risk of a type II error. Commonly practice is to take for L to be $L = 3$ making three-sigma control limits. If the distribution of the quality characteristics is reasonably approximated by the normal distribution, then it is assumed that 99.7% of points will fall inside the control limits while the system is in statistical control. In this way it is made good balance between type I error and type II error.

The first step in constructing the control chart requires analysis of preliminary data set which is assumed to be in statistical control. This phase is called phase I. In this phase it is very important to establish reliable control limits for phase II. In phase II, we use the control chart to monitor the process by comparing the sample statistic for each successive sample as it is drawn from the process to the control limits.

Performance of the control chart can be expressed in terms of its average run length (ARL). Essentially, the ARL is the average number of points that must be plotted before a point indicates an out of control condition. If the process observations are uncorrelated, then for any Shewhart control chart, the ARL can be calculated easily from

$$ARL = \frac{1}{p}, \tag{2}$$

where p is the probability that any point exceeds the control limits. That means for three-sigma control limits, $p = 0.0027$ is the probability that a single point falls outside the limit when the proces is in control and ARL = 370. That is, even if the process remains in control, an out-of-control signal will be generated every 370 samples, on average.

When we monitor only one qualitative characteristic of interest, we use *univariate control charts*. When we monitor more qualitative characteristics which are correlated we use *multivariate control charts* which take this correlation into account. There are many types of control charts which can be chosen depending on the nature of the process. In this paper is performed univariate analysis with MR (Moving Range) chart for individual measurements which actually contains two charts-upper chart is chart for individual measurements and lower chart is MR chart.

In many applications of the individuals control chart we use the moving range of two successive observations as the basis of estimating the process variability. The moving range is defined as

$$MR_i = | x_i - x_{i-1} | . \tag{3}$$

Let the $\overline{MR}$ be mean value of all moving ranges and $\overline{x}$ mean value of samples. Then the control lines for control chart for individual measurements are:

$$\begin{aligned} UCL &= \overline{x} + 3\frac{\overline{MR}}{d_2}, \\ CL &= \overline{x}, \\ UCL &= \overline{x} + 3\frac{\overline{MR}}{d_2}. \end{aligned} \tag{4}$$

Control lines for MR control charts are:

$$\begin{aligned} UCL &= D_4 \overline{MR}, \\ CL &= \overline{MR}, \\ LCL &= D_3 \overline{MR}. \end{aligned} \tag{5}$$

All constants in formulas (3) and (4) are in look up tables and depend on sample size [1].

3 Case-study: Boiler Furnace in Thermal Power Plant

In thermal power plants the most important tasks are increasing of energy efficiency and availability and reliability of existing power plants. The replacement of old and the installation of new distributed control systems improve the existing electric power systems and make them more effective and reliable. On the other hand, these computer systems for acquisition, monitoring and regulation of complex processes, such as boiler, turbine and generator in power plants, are opening space for simple superstructure and further optimization of some subsystems work, e.g., for the increase of availability and reliability of whole system. SCADA systems with appropriate PLC computers allow not only permanent monitoring and storing of all relevant physical quantities, but on the basis of these systems we can develop reliable protection, warning and regulation systems. The final goal of these computer architectures is the forming of optimized, more autonomic, reliable and safe processes.

Because of that, analysis of the control system of the combustion process and protection from explosions in the boiler furnace of thermal power plant helps in achieving this goal.

In this paper we analyzed in unit B2, the old and newly introduced system for measuring under-pressure differences in boiler furnace at various altitudes which have protection function of the boiler in thermal power plant TENT B.

Measuring and supervision of under-pressure difference at different altitudes is very important from two points of view. First one has protective nature, because big enough difference of these under-pressures shows stable combustion in boiler furnace, thus preventing explosion in boiler because of accumulated gasses or oxidation of unburned coal particles. On the other hand, after introducing protective under-pressure difference Δp in boiler furnace, it is possible to reduce significantly the consumption of fuel oil to support fire and it is reduced number of outages of blocks TENT B, due to extinguishing fires.

In this paper two systems for measuring of under-pressure difference on the boiler are analyzed. First, e.g., the former system for measuring of under-pressure difference measures three physical quantities (one on right and two on left side of boiler). Each of these measurements contains two impulse lines, where one line is attached to the boiler at elevation 72 m, second line is attached to the boiler at elevation 24 m, and both lines are then conducted in the boiler's environment and are placed in differential pressure sensor at elevation 44m. With these measurements we established empirical dependence of under-pressure difference from temperature in boiler furnace. Based on this dependency and after monitoring of combusting (of fire) in furnace, border values of under-pressure difference are established at which boiler protection works. It is required under-pressure difference $\Delta p > 300$ Pa for generation of permission for turning the mill on, if more than 40 m³/h fuel oil is turned on, or turning on of fuel oil for fire support if in drive are turned on at least three mills. In case where $\Delta p < 250$ Pa protective extinguishing of fire in boiler is necessary. Error of old system for under-pressure difference measurement shows gradient dependency of almost 2 Pa per one degree (–1.92 Pa/ºC). The error becomes more significant when temperature is bigger than 20°C and endangers usefulness of border values which are defined with protective functions of boiler (which is especially problem during the summer time). Then, environmental temperature of boiler becomes greater than 50°C, measurement error Δp is bigger than 100 Pa, in negative direction, and unnecessary fire extinguishing in boiler very probably. Experimental measurements show that old system of measurement has a systematic error.

Second, e.g., the newly introduced system for measuring under-pressure difference in boiler furnace is realized with two independent under-pressure measuring sensors at elevations 72 m and 24 m by forming their difference.

Experimental results showed that new system for measuring under-pressure difference eliminates systematic error, and as such presents reliable danger quantifier from explosion, so it can be used in protection logic during blocks starting, and also in theirs nominal regime of work.

In next section experimental results are shown in order to confirm advantages of new system in regard to old system of measurement.

4 Experimental Results

In order to analyze system for measuring under-pressure differences on boiler, we performed analysis of old and newly introduced system of measurement with MR control charts. Results were obtained from measurements which are recorded 16.12.2011. in typical modes of block B2 (nominal operation mode), during decreasing of block power and during increasing of block power, which we shall further call first and second measurements, respectively.

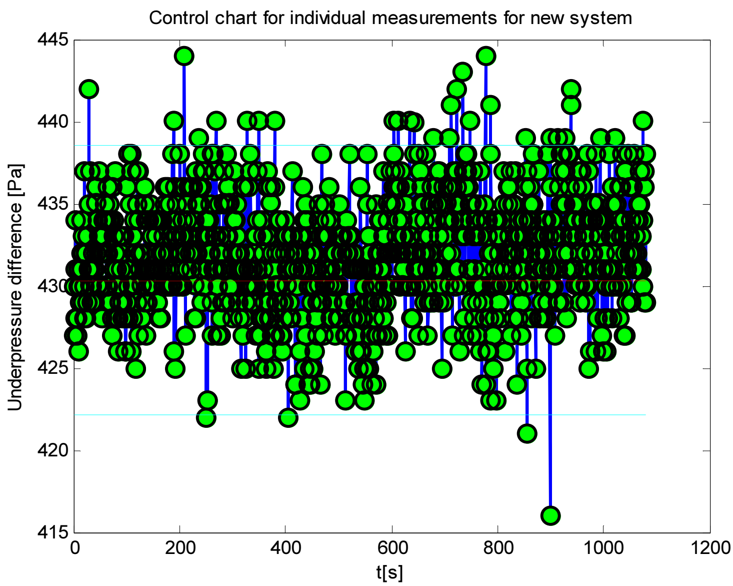


Fig. 2 – *Control chart for individual measurements for new system* (*first measurements*).

On Figs. 2, 3, 4 and 5 are shown control charts for individual measurements and MR charts for old and newly introduced system for first measurements. All control lines are established in phase I under statistical control. After careful analysis of Fig. 4, and after computing the autocorrelation function it is obvious that measurement of old system are correlated and that we cannot effectively apply MR charts on these measurements until we do not solve the autocorrelation issue.

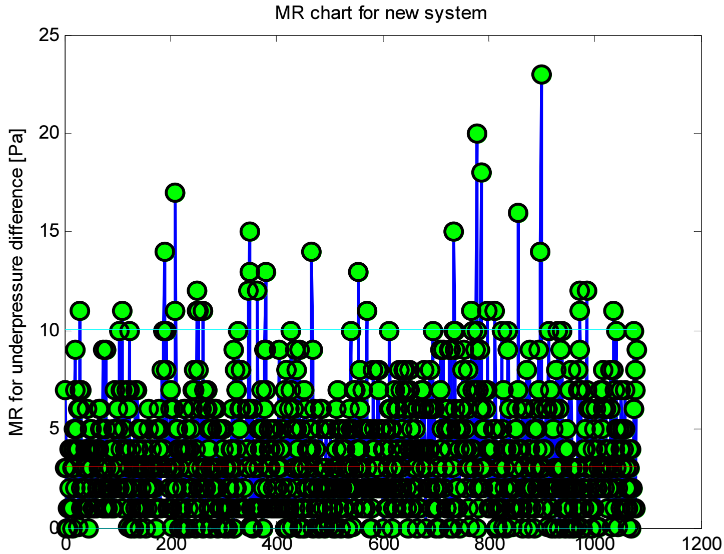


Fig. 3 – MR *chart for new system* (*first measurements*).

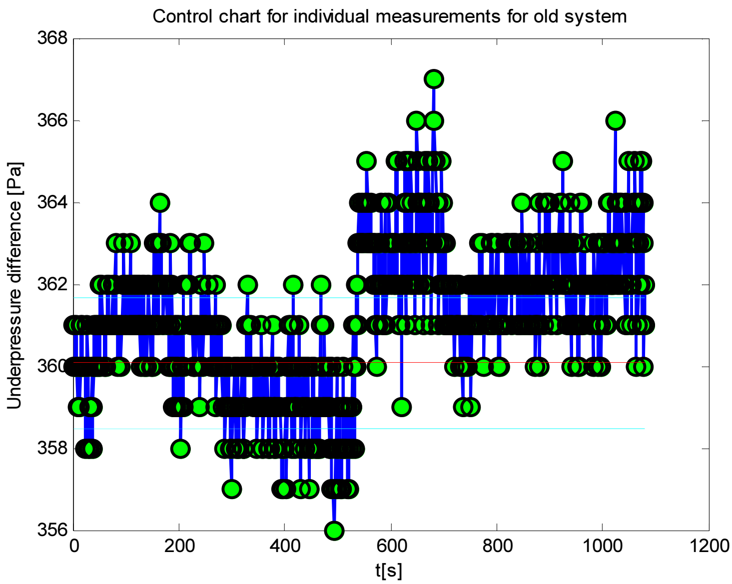


Fig. 4 – *Control chart for individual measurements for old system* (*first measurements*).

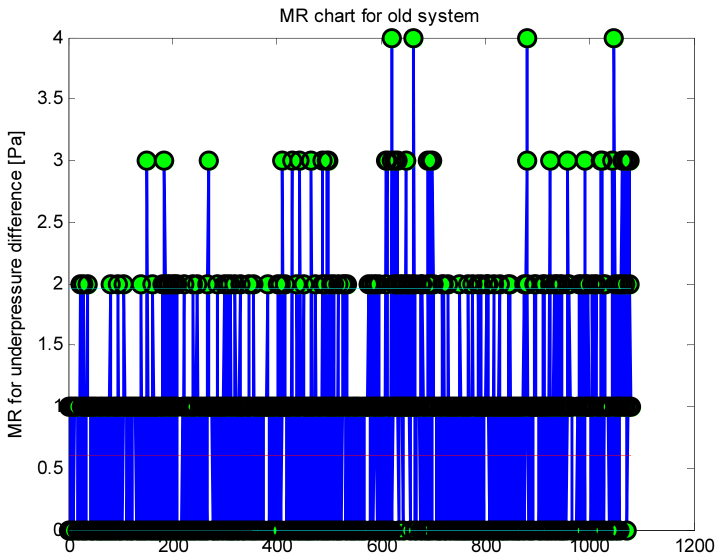


Fig. 5 – *MR chart for old system* (*first measurements*).

Independence of the observations is the most important assumption used during control chart design. Conventional control charts do not work well if the quality characteristics exhibit even low levels of correlation over time. Specifically, these control charts will give misleading results in the form of too many false alarms if the data are positively correlated. This point has been made by numerous authors [10, 13, 14]. There are many techniques that can be found in literature for solving this problem [1, 2, 10, 11]. Almost all approaches are based on analytical techniques. These approaches have proved useful in dealing with correlated data by direct modeling the correlative structure with an appropriate time series model (AR, ARIMA) and using that model to remove autocorrelation from the data and then applying control charts on residuals [15, 16].

Also, there is approach that is not based on the model, e.g a model-free approach [1] and it is applied in this paper. Runger and Willemain [12] proposed a control chart based on unweighted batch means for monitoring autocorrelated process data. The unweighted batch means chart breaks successive groups of sequential observations into batches, with equal weights assigned to every point in the batch. Let the *j*th unweighted batch mean be

$$\overline{x_j} = \frac{1}{b}\sum_{i=1}^{b} x_{(j-1)b+i} \,. \tag{6}$$

The important implication of equation (6) is that although one has to determine an appropriate batch size b, it is not necessary to construct an ARIMA model of the data. This approach is quite standard in simulation output analysis, which also focuses on inference for long time series with high autocorrelation.

Using formula (6) we created batch means and applied MR control chart on them. On Fig. 6 batch means control chart for individual values for old system and first measurement is shown, while on Fig. 7 MR batch means control chart for old system and first measurement is shown. b = 18 is chosen for batch size.

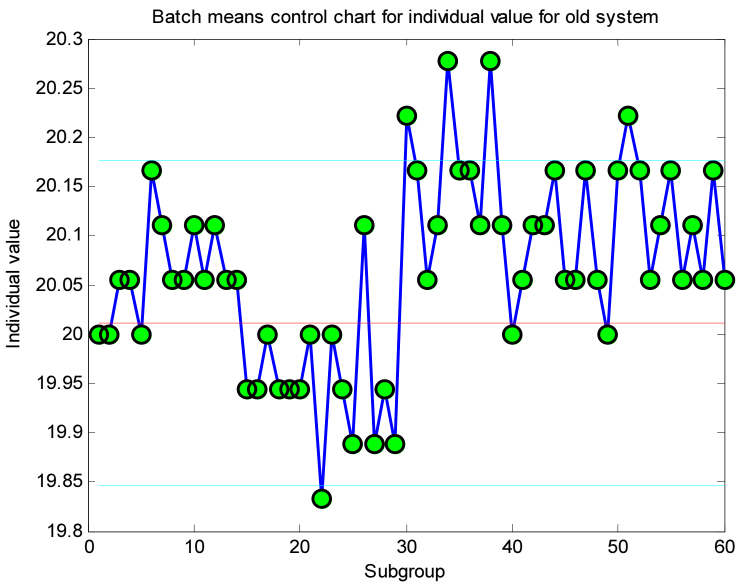


Fig. 6 – *Batch means control chart for individual values for old system* (*first measurements*).

After analysis of Figs. 6 and 7 we can conclude that the number of points which are within control lines is much bigger in regard to MR control charts from Figs. 4 and 5 where we could not apply control charts properly because of correlated data.

On Figs. 6 and 7 we can see that, although most of the points are within control lines, they do not form random pattern. We calculated the correlation matrix between under-pressure difference which is measured with old system of measurement and quantities of interest (block power at generator's output, boiler furnace's temperature at elevation +79 m, total air flow and total quantity of coal) so we could see which of these quantities has the biggest influence on old system of measurements. After we computed correlation matrix it was obvious that the biggest correlation coefficient (it is a negative coefficient) is between boiler furnace's temperature and the old system of measurement and the total quantity of coal and old system of measurement (also a negative coefficient).

Also, the correlation matrix between quantities of interest and the new system of measurement was calculated. The biggest correlation coefficient (negative coefficient) is between the total amount of fuel and new system of measurements, but this coefficient is significantly smaller at the new system in regard to the old system. For further analysis on Fig. 8 the change of temperature in boiler furnace and total amount of fuel for first measurements is shown.

Comparing Figs. 4, 6 and 8 we can see the direct influence of temperature change and total amount of fuel, on under-pressure difference change which was obtained with the old system of measurement. In fact, at the 336th sample there comes a sudden increase of temperature, which is manifested with the fall of points in regard to mean value at the same time. Then there comes a decrease of temperature which is manifested with the sudden rise of points, and then temperature starts easily to increase, and we can see the new fall of points. Also, the sudden rise of total amount of fuel from 600th to 800th sample has a big influence on points displayed from the 30th to 40th batch.

In order to confirm these conclusions control charts on second measurements were applied. Fig. 9 shows control chart for individual measurements for new system (second measurements).

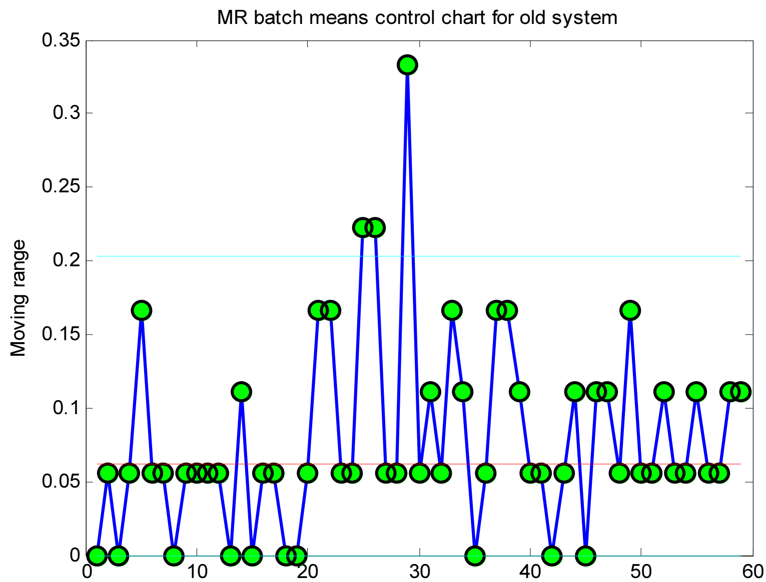
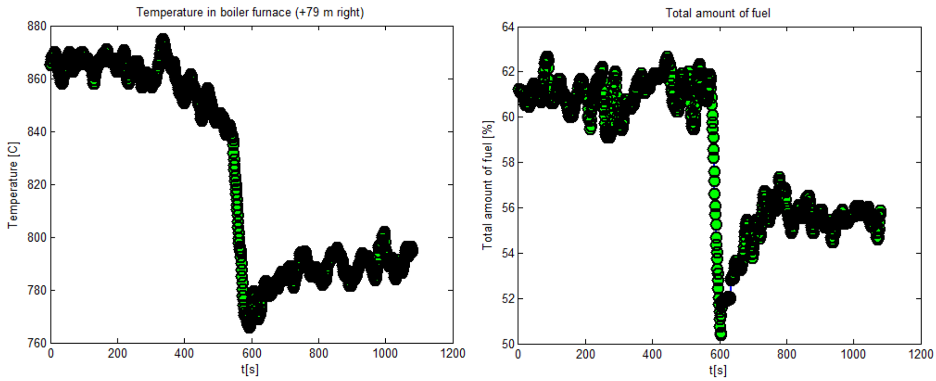


Fig. 7 – MR *batch means control chart for old system* (*first measurements*).



(a) (b)

Fig. 8 – (a) *Change of temperature in boiler furnace* (+79 m *right*) *for first measurements* (b) *Time dependency for total amount of fuel for first measurements.*

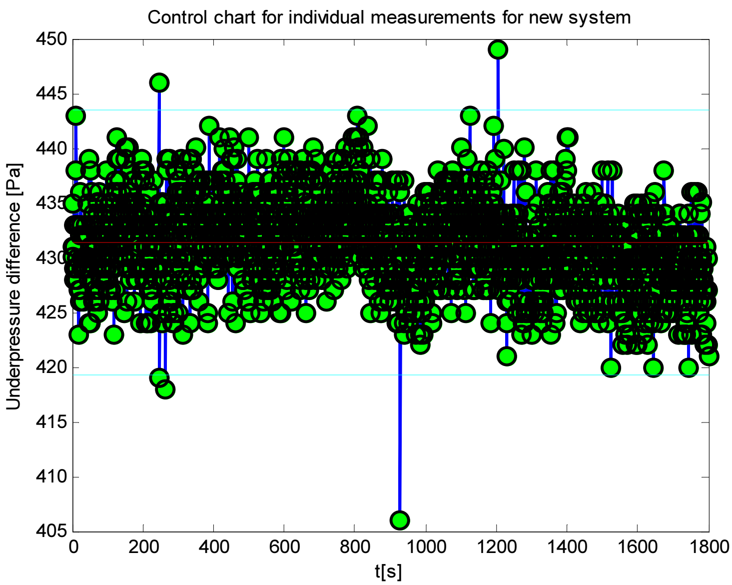


Fig. 9 – *Control chart for individual measurements for new system* (*second measurements*).

Fig. 10 shows MR chart for new system for second measurements. On Fig. 11 the batch means control chart for individual values for old system (second measurement) is showed. On Fig. 12 MR batch means control chart for old system for second measurements is shown. For batch size $b = 22$ is chosen.

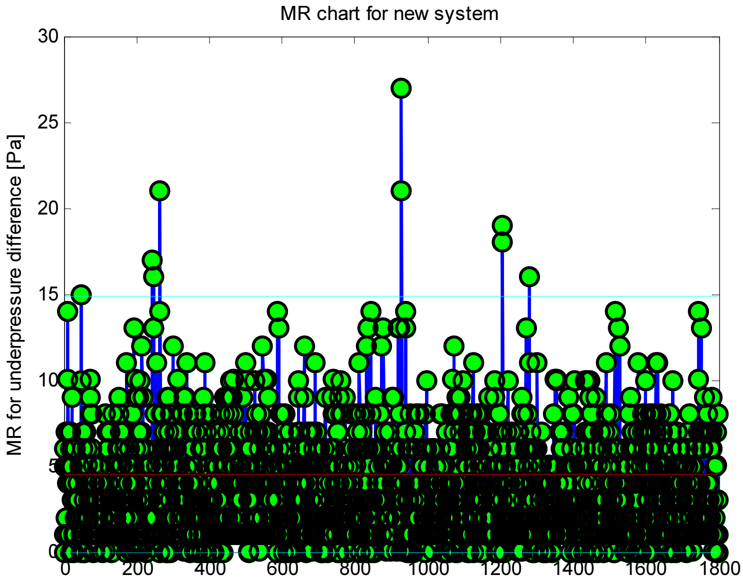


Fig. 10 – *MR chart for new system (second measurements).*

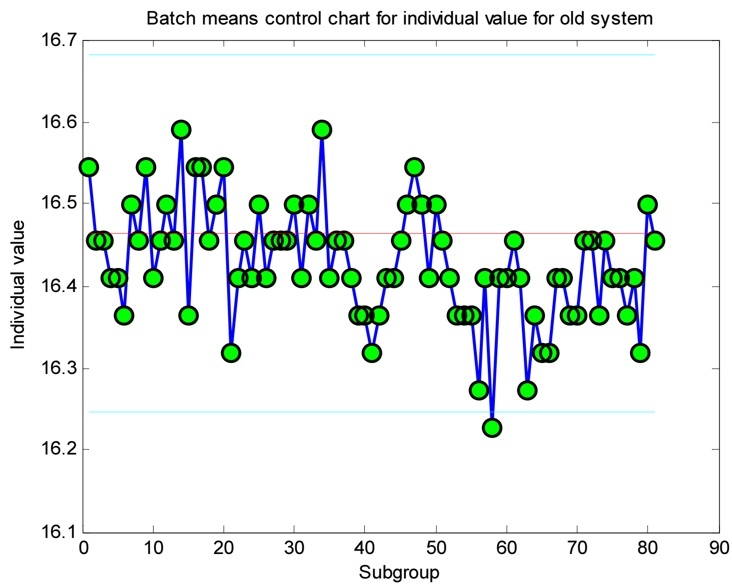


Fig. 11 – *Batch means control chart for individual values for old system (second measurements).*

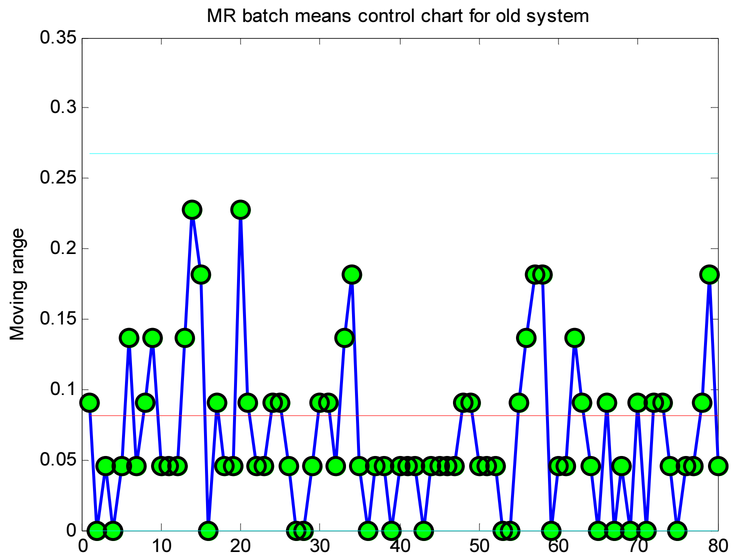


Fig. 12 – *MR batch means control chart for old system* (*second measurements*).

Again, in order to investigate which of quantities of interest has the biggest influence on new and old system of measurements, the correlation matrix was computed. Based on the correlation matrix it is obvious that on old and new system of measurement the biggest influence has total air flow, except that this correlation coefficient is significantly bigger for old, than for the new system.

For further analysis on Fig. 13 time dependency of total air flow is shown. Comparing Figs. 11 and 13 a big dependence of total air flow and old system of measurement is noticeable. This effect is especially expressed from the 800^{th} to 1000^{th} sample where sudden rise and fall of points on control chart happen. This influence is also noticeable at the new system of measurement, but it is much smaller compared to the old system of measurement.

Because of demonstrated strong influence of quantities of interest on old system of measurement, many false alarms could be seen. We applied control charts on measurements which are recorded during the nominal operation mode, e.g., while the process was stable and in control, and, again, old system showed irregularity of functioning. As we pointed out in Section 3 in case where under-pressure difference is $\Delta p < 250$ Pa protective extinguishing of fire in boiler is necessary. That means if protective under-pressure difference is not reliable than unnecessary extinguishing of fire is very probably which leads to block outage and very big financial and material costs. This analysis confirmed the unreliability of the old system of measurement.

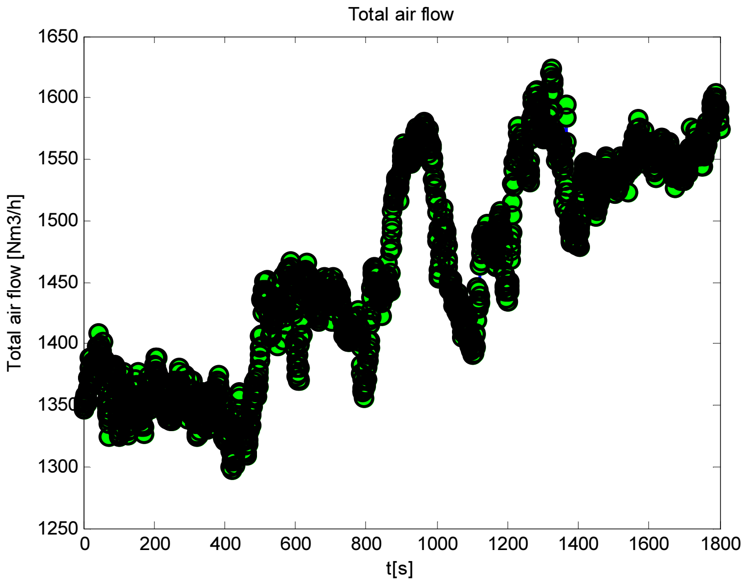


Fig. 13 – *Time change of total air flow for second measurements.*

5 Conclusion

After the detailed analysis of control charts that we applied on the old and new system of measurement, we can notice significantly stronger influence of quantities of interest (temperature in boiler furnace, total air flow and block power at generator's output) on the old system of measurement in regard to new system of measurement. Because of this fact reliability of the old system of measurement is questioned. Control charts confirmed that old system of measurement has a systematic error and endangers the reliability of the whole process.

The data from the new system of measurements have much noise, therefore the data have bigger variance and some points are outside of control limits. It is pretty sure that with adequate filtration of these data a big number of points that are outside of control limits would fall within the control limits. This is an explanation of false alarms on control charts for the new system of measurement.

During the control charts designing some problems were encountered. The first problem was the autocorrelation of data from the old system of measurements. We applied model-free approach and created batch means control charts in order to reduce the autocorrelation. In some future work there is possibility for constructing time series models and applying control charts on residuals.

The second problem that we had during the control chart designing was nonnormality of data from the old system of measurement. General model of control chart assume normal distribution of data and therefore if we choose three-sigma control limits then it is assumed that 99.7% of points will fall inside the control limits while the system is in statistical control. Very often this assumption is not valid, so control charts that do not assume normality of data are developed. They can be found in literature as *distribution-free* or *nonparamteric* control charts [17 – 20]. A key advantage of distribution-free charts is that the user does not need to assume any particular distribution (such as the normal distribution) for the underlying process and the in-control probability calculations and associated conclusions remain valid for any continuous distribution. This distribution robustness could be an advantage, particularly, in start-up situations where we usually do not have knowledge of the underlying distribution.

Also, there is a big problem with control chart designing of dynamic-behavior processes. A possible solution for this problem would be the making of adaptive control limits that follow system dynamics in the sense that big variation from central line which is consequence of system dynamics, not system fault, is treated as the nominal operation mode. In the literature one can find some solutions for this problem [21], but there is a lot of space for new ideas.

Control charts could be used as one more type of boiler protection from explosion in power plant. If we could collect big enough number of measurements for reliable estimation of control limits in phase I, which would be adaptive and totally follow process behavior, application of control charts in phase II, e.g. online data monitoring would be very efficient. Analyzing of points that are outside of control limits, or form nonrandom pattern on control charts we could notice that something is wrong with sensor system or maybe we could detect system fault. We could remove assignable causes and improve the process which is the main purpose of control charts.

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