# Two Smart Tools for Control Charts Analysis

*Adam Hamrol, Agnieszka Kujawińska*

**Abstract:**

*The paper deals with the analysis of process stability with the use of process control charts. A new idea of pattern recognition and two original methods of data processing, called OTT and MW have been described. The software application CCAUS (Control Charts - Analysis Unnatural Symptoms) supporting process control charts analysis with OTT and MW has been presented as well. Also the paper contains the results of the verification of the proposed methods performed on the basis of data obtained from two machining operations.*

***Keywords:*** *process, control chart, process stability, trend, pattern recognition.*

## 1. Introduction

The process control chart (PCC) is a statistical tool for supervising and improving process quality. Nowadays quality is usually viewed as conformance to customer needs and expectations. But from the pure manufacturing perspective quality means simply conformance to specifications (no defects) and additionally possible low variety (process stability). The other conditions mean that the product characteristics, e.g. dimensions, roughness, etc. obtained in the manufacturing process should not change from item to item.

In practice PCC can be viewed as a statistical procedure in which data is collected, organized, analyzed and interpreted in order to state whether the process is stable. In the past PCCs were applied to production processes, but it has evolved to any work where data can be gathered.

## 2. Process variability and process control chart

All processes (characteristics) show some variability. The variability results from two types of causes: the first, which can be usually recognized and controlled, are called special-causes. The second type called common-causes (random-causes), is inherent to the process and cannot be practically eliminated in an easy way.

Process control charts have to indicate if special-cause variation is present (Fig. 1). Usually PCC are the graphic presentation of process statistics like process average and process variances, which are calculated on the samples taken from the running process. Samples values result from measurements performed on chosen, usually viewed as critical characteristics of product or manufacturing process itself. The chart can show how the statistics change over time. An important part of PCCs are also called control (action) and warning lines, which enable to make decisions about process stability, even by the user without mathematical background [8], [3].

When the process is in statistical control (it is stable), the points on the control chart should follow a completely random pattern. The process is said to be out of statistical control when the pattern of the points provides hints to the source of the special-causes.

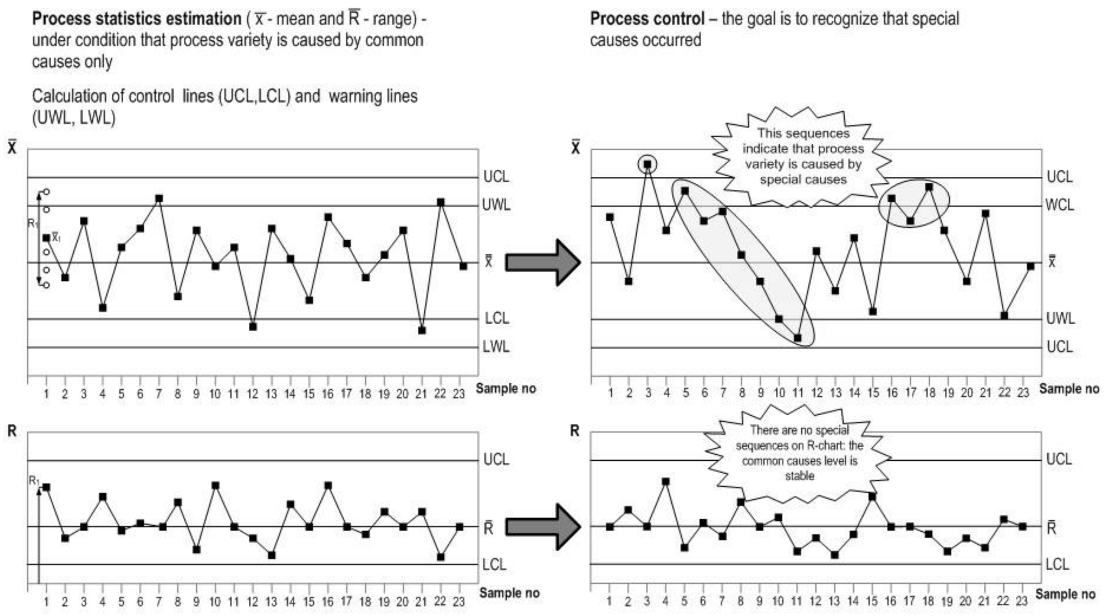


*Fig. 1. Idea of conventional process control chart (with action lines and warning lines) [3].*

There are many patterns indicating process instability. The identification of such patterns is oftentimes restricted to four cases: the point beyond the action line, trend, run, and shifts (the several points above or under the central line, here: $\overline{\overline{x}}$, $\overline{R}$ ) (Figure 1). The written sources on the subject indicate many other patterns. Most of them are not easy to identify and it is difficult to expect from the operator to be capable of making the right decision.

What to do with the process, which is under suspicion to be unstable, and how to take it under control is a matter of the process operator. Decisions of the operator are the result of his experience and sometimes the decisions are intuitive. There is a disadvantage of such a solution which consists in the necessity of constant observation of the pattern on the control charts by the worker whose attention should be focused mainly on the machine's operation. Another weakness of such solution is also insufficient knowledge of the operator of the sources of the special-cause variation and correcting actions. Moreover, there is always a risk that an experienced worker will resign from his post. Thus, the company loses his knowledge.

In order to solve the above-mentioned problems automatic pattern recognition should be applied (Fig. 2).

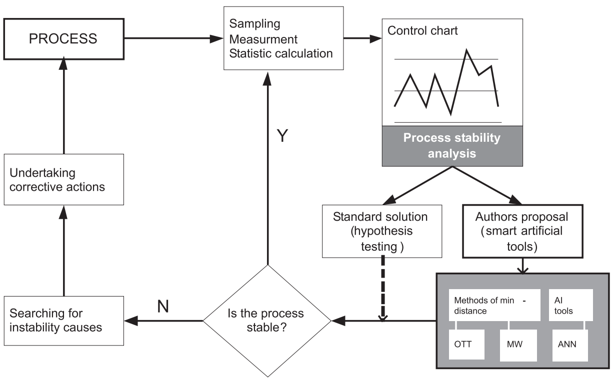


*Fig. 2. Process control using standard and smart tools of stability analysis.*

In such a case the man will no longer decide about the stability of the process and will no longer take up corrective actions to the process. However, it is possible to achieve by designing and programming certain methods of pattern classification on the charts. The pioneer researchers in this area are Cheng and Hueble from Arizona State University, Hamrol and Kalka from Poznan University of Technology.

## 3. Software aided SPC

During the last decades a lot of software aided statistical process control was devised. One if the most useful methods are the method called “3 zones”. It is strictly connected with the assumed normal distribution, imposes limitations concerning generating the unconventional signals (pattern). The “3 zones” method is applied in the well-known IT systems like Statistica, QDAS, and it is based on standards that were designed for the technological processes AT&T described in the year 1959. The zones are defined for the normal distribution and are multiplicity of standard deviation (also called sigma) process. The above limitation makes defining of non-standard signals such as; cycles, groups of points, mixtures, impossible. The method enables the researcher to define and recognize the symptoms on the chart by calculating probability of points occurrence in the following zones of control charts labeled as: A, B, C (Fig. 3), [2], [6].

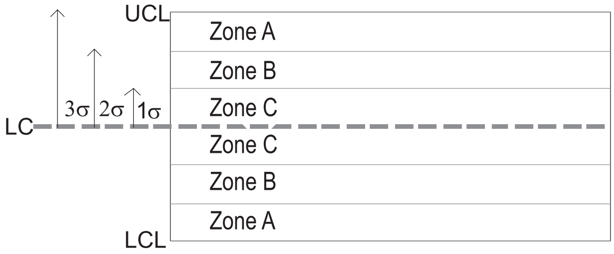


*Fig. 3. ABC zones on control chart.*

## 4. Authors' methods

The analysis of the methods concerning the pattern recognition has led the authors to develop theoretical assumptions and implement software for two new solutions. The new methods were called: One Two Three (OTT) and Matrix Weight (MW). The methods are called “smart” because they are based on very simple observation and do not need to use sophisticated mathematical tools. The first tool is based on the pattern recognition algorithm for control chart by Cheng and Hubele [1]. The other one is a completely new idea [5], [4], [7].

### 4.1. OTT methods

The idea is to correlate segments joining two successive points on the control chart with their slope in relation to the x - coordinate. To each segment an integer: 1, 2 or 3 is attributed. The integers reflect the slope direction, Figure 3. A resulting sequence of integrals attributed to successive segments is conceived as a picture, which reflects the process state from the point of view of its stability. The picture is further compared with patterns gathered in a pattern database, Figure 4. If the difference between the observed (under analysis) picture and the pattern is smaller than the fixed threshold value a signal about process instability is generated.

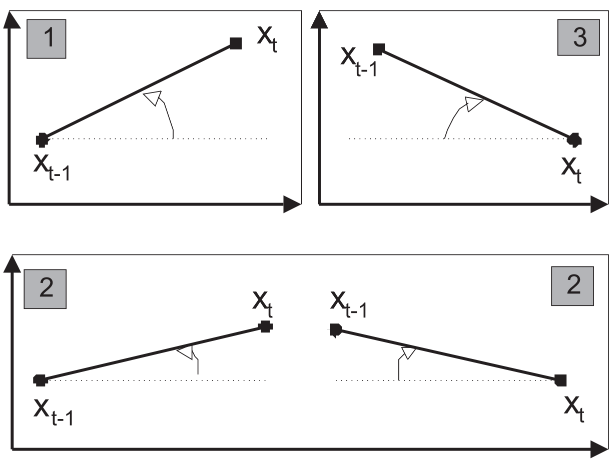


*Fig. 4. Associating the segment with its slope to the horizontal axis.*

The procedure of using OTT method is as follows (Fig. 5):

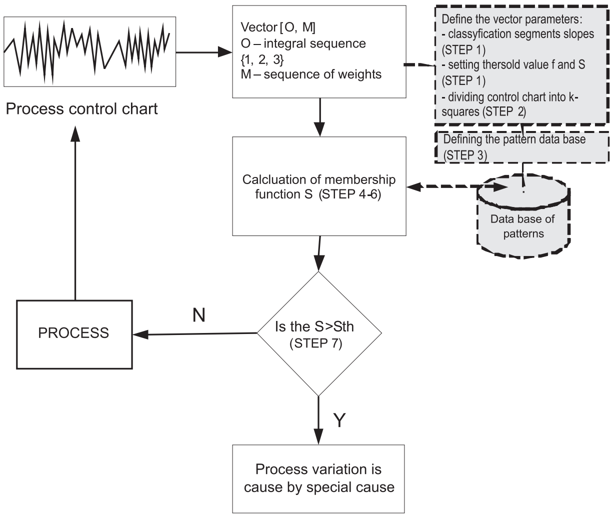


*Fig. 5. Flowchart of OTT method.*

**Setting parameters**

***Step 1.*** Classification of segments slopes into three classes according to the scheme in Fig 3. The slope is described by integers:
1 - (positive slope), if $(t_i - t_{i-1}) > \varphi$,
2 - (without slope), if $-\varphi < (t_i - t_{i-1}) < \varphi$,
3 - (negative slope), if $(t_i - t_{i-1}) < -\varphi$
where $\varphi$ is an arbitrary assumed value.

***Step 2.*** Dividing the control chart sheet into $k$ - stripes and attributing to each of them a coefficient (weight coefficient) $w_i$ from an interval $<1, k/2>$. The maximal weight $w_i$ is attributed to the central stripe, Fig. 6. It means that the value $w_i$ determines the location of strips. The number of stripes $(k)$ is to be fixed by an expert.

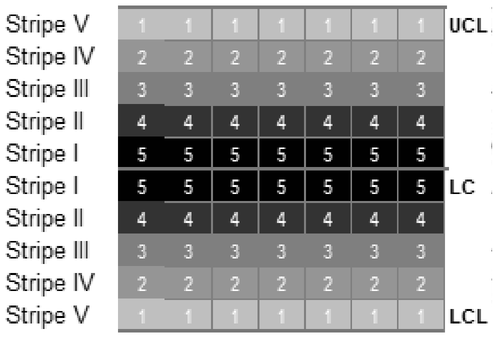


*Fig. 6. Dividing PCC sheet into k-stripes (e.g. $k=10$) and attributing to them the weights $w$.*

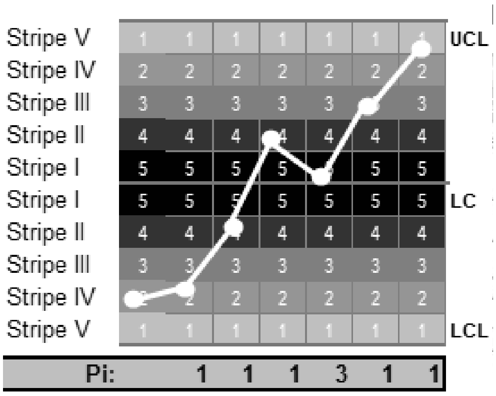


*Fig. 7. Examples of patterns.*

***Step 3.*** Defining the pattern database - $P$. A pattern $P_i$ is a sequence of integers out of 1, 2, or 3 (sequence of segment slopes). Each combination of the integers is correlated with the process instability symptoms, Fig. 7.

**Recognizing process instability.**

***Step 4.*** A picture on PCC as a sequence of points (see Fig. 1), which is to be examined in order to make a decision about the process stability, is presented as a vector $[O_i; M_i]$. The component $O_i$ is a sequence of integers 1, 2 or 3 and the component $M_i$ reflects the location of the vector on PCC sheet. $M_i$ is the product of weights of areas in which the end and beginning of the $i$-segment under observation is located: $M_i = w_i * w_{i+1}$.

***Step 5.*** The vector recorded in the way defined in Step 4 is compared in a row with the patterns $P_i$, defined earlier in the database. The distance $d_i$ between the pattern $P_i$ and the picture $O_i$ is examined. The distance is a measure how similar the examined vector and the specific pattern are. For each segment of the analyzed vector the value of:

$$d_i = \begin{cases} 0 & where \quad P_i - O_i = 0 \\ 0{,}5 * g_i & where \quad P_i - O_i = 1; -1 \\ g_i & where \quad P_i - O_i = 2; -2 \end{cases}$$

is calculated, where $g_i = \log M$,

***Step 6.*** Similarity coefficient $S$ is calculated,

where $L$ - maximum value of sum of $d_i$ (e.g. for chart with ten stripes the maximum sum of $d_i$ is equal seven),

***Step 7.*** Decision making: process is unstable if $S > S_{th}$. When the calculated $S$ value is greater than the limit value $S_{th}$ and is close to 1, the analyzed pattern is said to be strongly similar to the given pattern in the database. The steps presented above concern the trends only. In order to assign the right pattern class to shifts or fluctuations (Fig. 1) equation must be realized:

$$\sum_{i=1}^{n-1} M_i \le (n-1)(w_l w_{l-1})$$

An example of using the method described is shown in Fig. 8.

**4.2. The MW method**

The idea of MW (Matrix Weights) method is oriented on processes in which the instability is revealed, first of all, in the form of trends. In an analytical approach searching for a trend means comparing subsequent values of a given sequence of points on the PCC sheet. Denoting by $x_i$ subsequent values of a variable $X$, a rising trend occurs if the following condition is met: $x_1 < x_2$ and $x_3 < x_4$ and … and $x_{n-1} < x_n$.

Unfortunately, in practice trends have seldom such a pure shape. For example, the second sequence in Fig. 9 can be defined by the relations:
$x_1 < x_2$ and $x_3 > x_4$ and $x_3 < x_4$ and $x_4 > x_5$ and … and $x_{n-1} < x_n$.

The information depicted by the above equation is not convenient to make a proper decision about the process

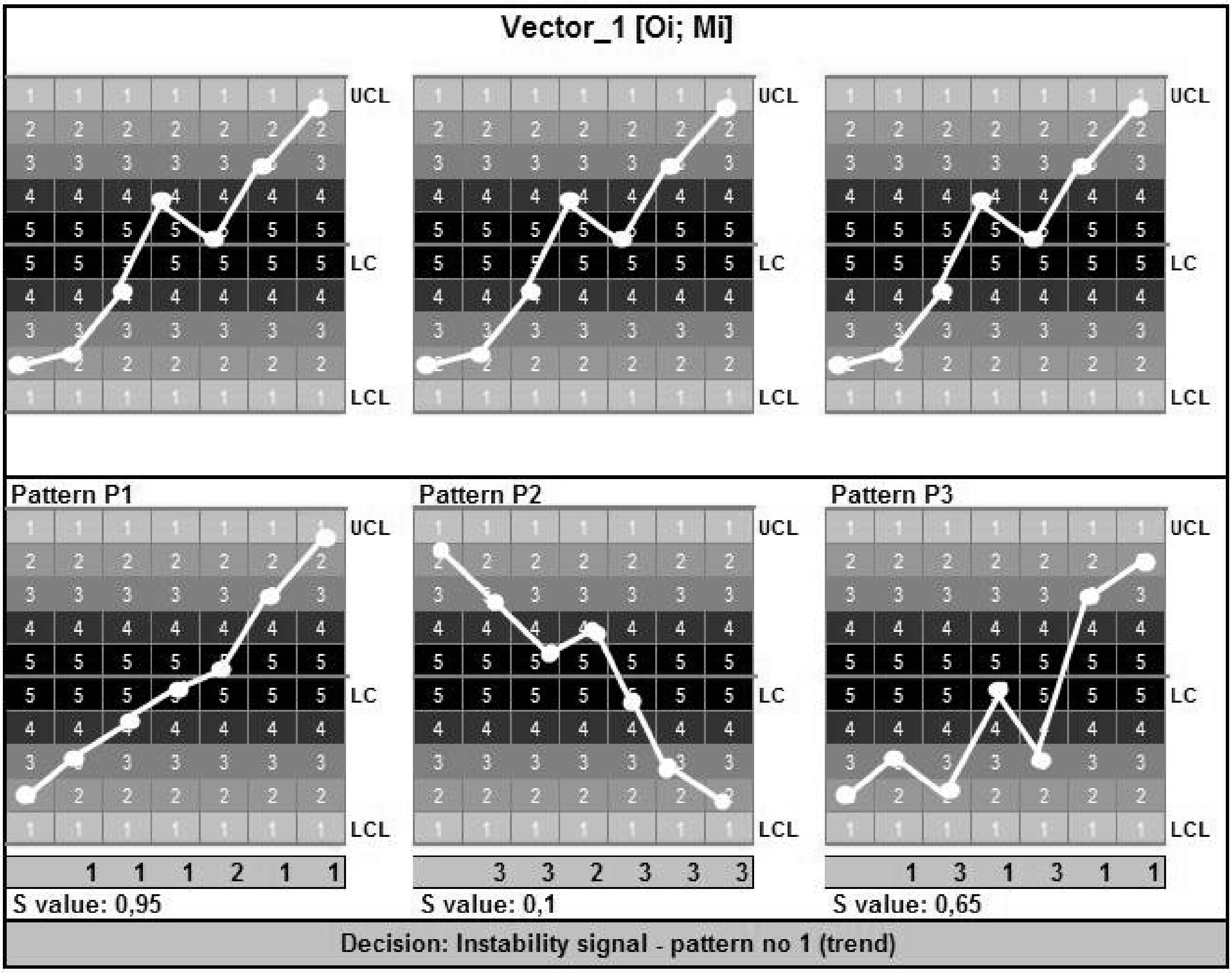


*Fig. 8. Example of pattern recognition.*

stability because there is an indefinite number of various combinations. But one can notice that no matter how the points are situated towards each other they are located in a specific strip on the control chart. This observation is a starting point to the method described below. The developed method is based on the division of the chart into the matrix of $[k \times n]$ size ($k$-columns, $n$-lines), and each of them is assigned the weight $w_i \in <0, 1>$.

The idea of the method is shown in Fig. 10.

**Preparation stage**

***Step 1.*** Dividing the PCC field into matrixes of $[k \times n]$ dimensions.

***Step 2.*** Attributing to the matrix fields weights $w_i \in <0, 1>$. Distribution of the weights is correlated with specific symptoms of process instability. Defining the pattern database.

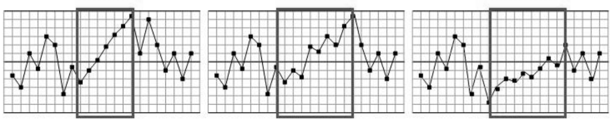

*Fig. 9. Three examples of trends.*

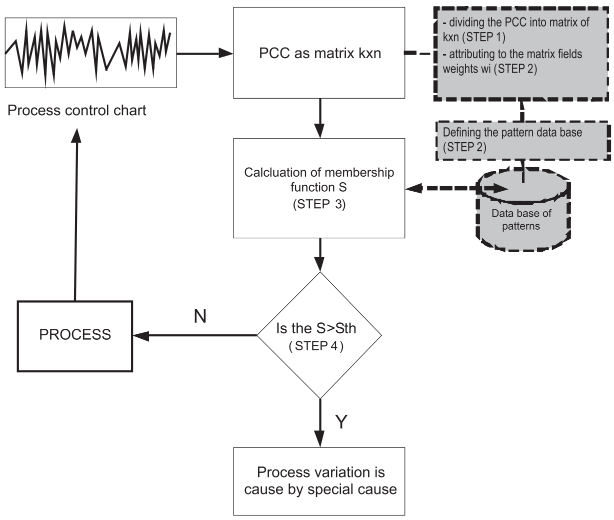


*Fig. 10. Flowchart of MW method.*

**Recognition stage**

***Step 3.*** For a given sequence of points on PCC sheet a value is calculated. The $S$ measure is a sum of weights $w_i$ attributed to the points from the sequence.

***Step 4.*** Comparison of $S$ with the threshold value $S_{th}$ that is fixed by an expert. If $S$ has a greater value or equals to the limit value then there is a signal produced indicating the appearance of the pattern.

The method limitation is the necessity of matrix creation for each class of patterns as well as choosing the limit value Sth that determines the picture's recognition as a symptom (Fig. 11).

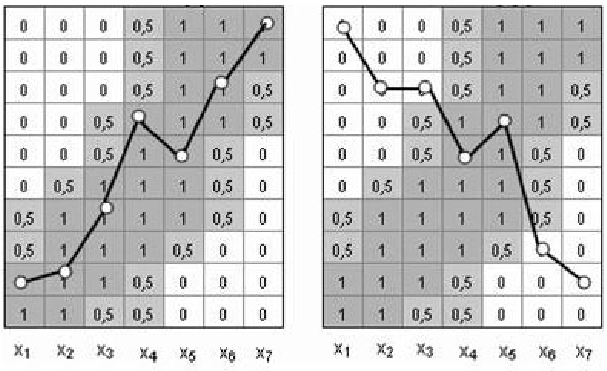


*Fig. 11. Example of rising and falling trend matrix.*

### 4.3. Verification of the developed methods

Verification of the developed methods was carried out on the set of data obtained from the grinding process (process 1) and from the superfinish of the surface of TV screen (process 2).

In order to verify the efficiency of the methods, they were programmed in DELPHI 7.0 language and the software was called CCAUS: Control Charts – Analysis Unnatural Symptoms. The software enables: introduction of the measurement data, carrying out basic statistical analysis of the data, creating control charts, analysis charts and search for the symptoms by using OTT and MW methods, creating the database with the sources of process instability, creating database that would undertake correction. The main aim of CCAUS is the analysis of control charts. The analysis is carried out by the comparison of the pictures created on the chart with their defined patterns set by an expert in the database.

The verification was carried out according to the following plan:

- defining $k$-element set of patterns for the process 1 and 2 (P1, P2). The patterns were defined according to the instructions considering the use of the control chart that are obligatory in given companies and from which the information about the process was obtained. In both cases, there were 7-element patterns obtained;
- collecting data from the processes (V1, V2) as well as the results of picture recognition by the operator of the machine (OP);
- data class analysis V1, V2. Marking all the patterns indicating the changes in the stability of the process, according to the experts and the person who is responsible for the process;
- recognizing the symptoms in the classes V1 and V2 by applying the OTT method, MW method as well as artificial neuron networks ANN (Artificial Neural Networks).

Comparing the effectiveness of recognition by set measures: $MP_r = \frac{n_r}{n}$ and $MB_r = \frac{nb_r}{N}$

where:
$MP_r$ – indicator of correct recognition,
$MB_r$ – indicator of incorrect recognition,
$n$ – the number of all the patterns,
$n_r$ – the number of patterns recognized by the $r$-method,
$N$ – the number of all the indications,
$nb_r$ – the number of incorrect indications of $r$-method.

The results of the verification are presented in Table 1 and in Fig. 13. As a benchmark the recognition by using a neural network based algorithm (ANN) was applied.

*Table 1. Verification results.*

| | Methods/ Value of measure $MP_r$ [%] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Process 1 | | | | Process 2 | | | |
| Pattern | OP | OTT | MW | SSN | OP | OTT | MW | SSN |
| Run + (RR) | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Run – (RM) | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Trend + (TR) | 93 | 99 | 100 | 99 | 97 | 99 | 100 | 99 |
| Trend - (TM) | 91 | 98 | 100 | 98 | 92 | 97 | 99 | 98 |
| Shift up – SU | 90 | 90 | 100 | 99 | 90 | 89 | 98 | 99 |
| Shift down – SD | 85 | 92 | 96 | 100 | 87 | 92 | 98 | 100 |
| Group 2from3 | 48 | 90 | 80 | 96 | 53 | 96 | 93 | 96 |
| Mixture – MIX | - | - | - | - | 51 | 74 | 91 | 92 |
| **Average** | **86,71** | **95,57** | **96,57** | **98,86** | **83,75** | **93,38** | **97,38** | **98,00** |

The values of MB measure were not presented because in all the cases they were less than 1%.

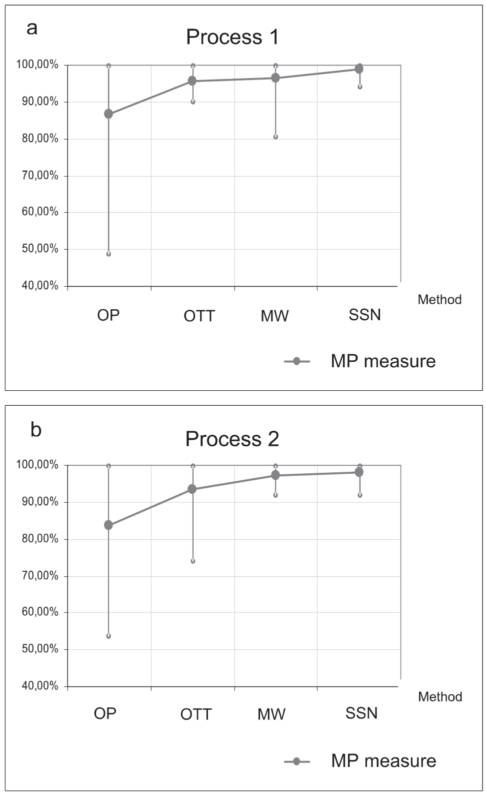


*Fig. 13. The values of MP measure for OP-, OTT-, MW- and SSN-methods.*

The weakest of the methods is the traditional method (assessment of operators, OP) – the least value of MP measure (Fig. 5).

The percentages of correct recognition by the use of MW and SSN methods are almost approximating each other but there is a slightly better performance of artificial neural network (as well as for process 1 and 2).

The verification of the methods efficiency has confirmed that the operator is a weak element in the process' analysis of the control charts. The operator performs well when dealing with a trend, run or shift pattern but not with the mixture type pattern and 2 from 3 points in the warning area. The classification based on the OTT method provides the researchers with an average result and it is much better than the man's recognition. Similarly to the operator, the OTT method does not “like” the models called mixtures. The best results were obtained for artificial neuron networks and the matrix importance method.

## 5. Conclusions

The control charts are the pictures of the process stability. They enable the authors to use the techniques of picture recognition in the process of the charts analysis. Developing the OTT and MW methods provided the author with good results of process' state recognition. They proved to be more efficient than the operator - the man.

The developed methods enable the experts to create unconventional patterns of instability processes, which significantly widens the possibility of their application.

**ACKNOWLEDGMENTS**

This work was supported by the AGH University of Science and Technology under Grant No. 11.11.120.612.

**AUTHORS**

**Adam Hamrol*, Agnieszka Kujawińska** - Institute of Mechanical Technology, Poznan University of Technology, ul. Piotrowo 3, 61-138 Poznań. Tel. tel: (61) 665 2774 (Mr Hamrol), tel: (61) 665 2798 (Ms Kujawinska). E-mail: adam.hamrol@put.poznan.pl

* Corresponding author

### References

[1] Cheng Ch., Hubele N., “A pattern recognition algorithm for an x control chart”, IIE Transaction, no. 28, 1996.

[2] Dietrich E., A. Schulze A., *Statistic methods for measuring resources' qualification*, Notika System: Warsaw 2000.

[3] Hamrol A., *Quality Management with Example*, PWN: Warsaw, 2008.

[4] Hamrol A., Kujawińska A., *New method of control charts analysis*, Poznan University of Technology ATMiA: Poznań, 2006.

[5] Hamrol A., Kujawińska A., “Solving of tasks symptoms classification with neural networks”. In*: Komputerowo Zintegrowane Zarządzanie* (Computer Integrated Management), vol. 1, WNT: Warsaw, 2003, pp. 375-382.

[6] Juran J.M., Godfrey A.B. Juran's Quality Handbook, McGraw-Hill, 2000.

[7] Kujawińska A., “Automation of the Quality Control Charts”. In: *13th International DAAAM Symposium “Intelligent Manufacturing & Automation: Learning From Nature”*, Vienna University of Technology, Vienna, Austria, 2000.

[8] Woodall W.H., “Controversies and Contradictions in Statistical Process Control”, *Journal of Quality Technology Session*, 2000.